The Power of Facial Expressions

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Publication date:
2017

Document Version
Publisher's PDF, also known as Version of record

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The research reported in this thesis was sponsored by the Netherlands organisation for international cooperation in higher education (Nuffic) programme, dossier no. CF 7553; NFP-PhD.11/238

SIKS Dissertation series No. 2017-30. The research reported in this thesis has been carried out under the auspices of SIKS, the Dutch Research School for Information and Knowledge Systems

TiCC Ph.D. Series No. 55.

ISBN/EAN: 978-94-6295-730-5

Model of the cover and the back cover by courtesy of David Tuhurima.

Cover design by: ProefschriftMaken.nl || www.proefschriftmaken.nl
Printed by: ProefschriftMaken.nl || www.proefschriftmaken.nl
Layout by: ProefschriftMaken.nl || www.proefschriftmaken.nl
Published by: ProefschriftMaken.nl || www.proefschriftmaken.nl

THE POWER OF FACIAL EXPRESSIONS

PROEFSCHRIFT

ter verkrijging van de graad van doctor
aan Tilburg University
op gezag van de rector magnificus,
prof. dr. E.H.L. Aarts,
in het openbaar te verdedigen ten overstaan van een
door het college voor promoties aangewezen commissie
in de aula van de Universiteit
op vrijdag 29 september 2017 om 10.00 uur

door
WILMA LATUNY,
geboren op 6 april 1978 te Ambon, Indonesië

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PREFACE

Performing Ph.D. research and writing a thesis is as a journey. At one day you start and at another day you hope to finish. In my case, the first day was in 2011. The research was really a journey. My first idea was using data mining for predicting seaweed selling prices. However, I did not get the project running. My main difficulty was collecting the appropriate data. Meanwhile, I was given to understand that data mining is closely related to pattern recognition. So, I looked for areas in which many data were available and where pattern recognition could be applied in a profitable way. During that period in 2012, I started to create my own database from publicly online sources, such as www.youtube.com. Thus, my journey was restarted by investigating video data of human performers.

Thereafter the idea arose to do exploratory analysis of human facial expressions from video or photo data. By employing statistical analysis and data mining techniques I addressed the following problem statement: “What is the power of the facial expressions in competitive settings?”. Competitive settings appear, among others, in beauty contests and music competitions. I operationalised the research on four competition domains namely: Miss World International Competition, Mister World International Competition, International Piano Competition, and JKT48 (JaKarTa 48) Leadership Singing Competition.

The findings of my research revealed the following four results: (1) facial expressions contribute to attractiveness ratings but only when considered in combination with sexual dimorphism (femininity), (2) thin slices of dynamic facial expressions contribute to the attractiveness of males in similar way as static images do, (3) facial expressions allow the identification of the winning musician, and (4) facial expressions can predict a direct relation to the assessment of leadership. In summary, the thesis contains the following three scientific contributions: (a) four new findings concerning the power of facial expressions in competitive settings, (b) a variety of small contributions to the existing literature on facial expressions, and (c) a measurement comparison of facial expressions as assessed by human beings and computers.

I would like to recognise the help of many people and institutions. First of all, I would like to thank my supervisors Professor Eric. O. Postma and Professor H. Jaap van den Herik for their valuable guidance and encouragement they gave me. God bless you and your families.

Second, I am grateful to the Netherlands organisation for international cooperation in higher education (Nuffic) for their sponsorship, which enabled me to undertake my Ph.D. project. I also thank the Tilburg University, the Maastricht School of Management (MSM) the Netherlands, and the University of Pattimura Ambon Indonesia, for giving me the opportunity to study.

Third, my sincere thanks go to all my friends and family members. In particular, to my parents Izaak Latuny and Monika Nussy, and to my brother Richard Latuny and his family (Felly, Abigail, and Zipora), I would like to express my sincere thanks for

their support that I received throughout the Ph.D. journey. To my aunts Josephina Sopacua and children, Kristin Toisuta and husband, to my uncles Johan Nunumete, wife, and children and Henoch Nunumete, wife, and children, I also would like to express my thanks for their support and their nurturance during my study in Maastricht and Tilburg.

Lastly, I would also like to acknowledge the support of the staff of DCI and TiCC of the Tilburg School of Humanities, particularly my thanks go to Professor dr. A.A. Maes as the Chair of DCI. Also, I wish to acknowledge the excellent support received from the staff members, more specifically from Eva, Lauraine and the former staff members Jachinta and Joke. Finally, I wish to acknowledge the other excellent support that I received, namely from the Research Department of the Maastricht School of Management (MSM). I would like to thank in particular the dean of MSM Prof. dr. W.A. Naudé as well as Patrick Mans and Sandra Kolkman as former manager and senior research staff in MSM and also Rocco Muhlenberg as a senior officer research and IT Education.

Tilburg, April 17, 2017

Wilma Latuny

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LIST OF ABBREVIATIONS

AF	Average Femininity
AFC	Automatic Facial Coding
API	Application Programming Interface
AUs	Action Units
CERT	Computer Expression Recognition Toolbox
CK	Cohn-Kanade (AU-coded Facial Expression) (Expert experiment)
Emo	Emotional Expression
FACS	Facial Action Coding System
HRM	Human Resource Management
ILT	Implicit Leadership Theory
JKT48	JaKarTa48 = a group of singing competition JaKarTa48 from Indonesia
JSON	JavaScript Object Notation
KMO	Kaiser-Meyer-Olkin
LOO	Leaving-One-Out
MPEG−4	Motion Picture Experts Group Layer−4
MSE	Mean Squared Error
N	Number of Sample
NV	NoVice Experiment
p	p-value (probability)
PCA	Principal Component Analysis
PS	Problem Statement
r	Coefficient Correlation
RDF	Random Decision Forest
RQ	Research Question
SD	Standard Deviation
SDM	Supervised Descent Method
URL	Uniform Resource Locator

1 INTRODUCTION

Setting the scene is important for every research topic. Ours is no exception. The first scene of our research is as follows. A selection committee is willing to receive the first candidate for the recently established professorship of data science in society. The members of the committee are well prepared by a university trainer from whom they learned that some individuals might make a big impression on other people, whereas others do not. Frequently, charismatic individuals benefit from their impressive appearances in an election procedure, a contest, or a competition. But to what extent do such persons really have a clear advantage over the other candidates? The university trainer is a professional lecturer. She had warned the members of the committee for fast conclusions and stressed that keeping a balanced consideration is always better. However, a balanced consideration takes time, and first impressions can be formed in a short period of time, say less than 30 seconds (cf. Ambady & Rosenthal, 1992). First impressions are often formed subconsciously using facial appearances (cf. Bar, Neta & Linz, 2006; Olivola & Todorov, 2010; Tom, Tong & Hesse, 2010). As every well-trained candidate knows: facial appearance has been shown to have a large influence on impression formation. To be more precise facial attractiveness is associated with positive traits and facial unattractiveness with negative traits (Miller, 1970). Thus, facial expressions are known to affect impression formation (see Bar et al., 2006). Now the question arises: how can a candidate use the facial expressions in a beneficial way in a competitive setting?

In section 1.1 we mention three examples of empirical studies showing that an individual's facial expressions influence the assessments. Then, in section 1.2 we discuss the effect of the context. This completes our basic introduction to the topic. At that point we will give an outline of the contents of the first chapter.

1.1 THE INFLUENCE OF FACIAL EXPRESSIONS

The first example is an established study by McHugo, Lanzetta, Sullivan, Masters and Englis (1985), who presented college students video excerpts of Ronald Reagan displaying different emotions. Reagan's emotional expressions affected the self-reported emotions of the students. When Reagan displayed happiness or reassurance, the students reported that they experienced positive emotions, whereas in case of a display of anger or threat they reported negative emotions. These emotional responses have consequences for the formation of impressions.

The second example is a recent study by Ruben, Hall and Schmid Mast (2015) who examined how smiling affects the hireability of job applicants. In particular for jobs with a serious demeanor, the researchers found that the amount of smiling was inversely proportional to hireability. Applicants who were more likely to be hired smiled less, especially in the middle of the interview as compared to the beginning and the end. Importantly, the type of job was to find a moderator for the effect of smiling on hiring, which indicates the importance of a context on the interpretation of facial expressions.

The third example is a rather recent computational study of online conversational videos (vlogs). Biel, Teijeiro-Mosquera and Gatica-Perez (2012) collected 281 vlogs which were assigned Big-Five personality assessments by Mechanical-Turk workers (5 assessments per vlog). The Big Five traits are: Openness to experience (O), Conscientiousness (C), Extraversion (E), Agreeableness (A), and Neuroticism (N) (see Biel et al., 2012). Using the Computer Expression Recognition Toolbox (cf. Littlewort, Whitehill, Wu, Fasel et al., 2011) (see also section 1.4) and machine learning methods, Biel et al. (2012) found that facial expressions of emotion were related to personality assessments. In particular, Extraversion could be predicted better than so far. Apparently, previous methods were at that time (2012) surpassed by the CERT toolbox.

These examples illustrate that facial expressions may contribute to impression formation. As is evident from the second example, the context poses a difficulty when studying the impact of a person's facial expression on assessments about his or her quality.

1.2 THE EFFECT OF THE CONTEXT

There are two main ways in which context has an effect on inferring traits from facial expressions: (1) the effect that context has on the perception of facial expressions and (2) the effect that context has on the generation of the facial expressions. We briefly discuss both contextual effects.

First, the effect of the context on the perception of facial expressions may be illustrated by a cinematographic example. In a famous demonstration of the Kuleshov effect in movies (see Prince & Hensley, 1992), film director Alfred Joseph Hitchcock showed a scene of his own face with an expression that slowly changed from neutral to a subtle smile. This scene was preceded by either a scene of a mother with a baby or by a scene of an attractive female in a bikini. In the first case, the impression of Hitchcock was that of a gentle and kind man, whereas in the second case, the impression was that of a dirty old man [1]. As this example illustrates, one facial expression can lead to opposite assessments or impressions.

Second, the effect of the context on the generation of the facial expressions is closely related to the social context. A classical experimental study of the effect of the social context on the perception of faces is performed by Cline (1956). He presented participants with drawings of pairs of faces with different expressions. For instance, he assessed the ratings of a frowning face paired with a glum face and compared that with the ratings of a frowning face paired with a smiling face. The comparison revealed that in the presence of the glum face, the frowning face seemed to belong to an initiator, whereas in the presence of a smiling face it seemed to be the face of a

1 Hitchcock Explains the Kuleshov Effect to Fletcher Markle 1964: https://youtu.be/96xx383lpiI

follower. The reason for this change in assessments of the same facial expression is at least partly due to the change of the social context. Participants rate the expressions in the light of the inferred social interaction between the two faces in much the same way as happens in the Kuleshov effect (cf. Prince & Hensley, 1992). Modern theories addressing the effects of context on the perception of facial expressions emphasise the dynamic interplay of perceptual cues and cognitive states (see Adams, Ambady & Nakayama, 2011; Freeman & Ambady, 2011).

Context also affects the facial expression behaviour of individuals. Cultural and social norms dictate how to respond to a given situation. According to Ekman and Friesen (1969), humans learn to modulate their emotional (facial) expressions during their childhood. They should behave according to a set of rules referred to as *display* rules (Ekman & Oster, 1979). These rules apply to a large variety of situations. For example, flight attendants (Hochschild, 2003) and bill collectors (Rafaeli & Sutton, 1991) are required to have facial expressions that agree with their occupational positions, i.e., friendly and serious expressions, respectively.

1.2.1 Our Research Domain

As the above considerations show, the study of the power of facial expressions is hampered by the possible distorting effect of context. Without controlling for context, it is hard to interpret measurements of facial expressions. Therefore, in this thesis we focus on the study of the power of facial expressions in a restricted context, namely the context of competitions. As pointed out by Ekman, competitions are associated with specific display rules. For example, whereas winners in American sports may smile, the winner of a Miss World contest must cry (Boucher, 1974).

Our experiments will focus on the analysis of facial expressions in four competitive contexts: female pageant contests, male pageant contests, a music contest, and a leadership contest. We assume that within each of these contests and contexts, the display rules are fixed. For instance, in a pageant contest, the display rule may be to smile or to transmit a positive expression. Alternatively, during a piano concerto the display rule may dictate the performer to exhibit a range of facial expressions that are congruent with the emotional spirit of the music. Finally, in a competitive situation where individuals are assessed on their leadership skills, serious expressions are assumed to be prevalent.

1.2.2 The Power of Facial Expressions

If our assumption holds, the competitive contexts allow us to study *the power of facial expressions*. We believe that facial expressions can be decisive in competitive settings. Therefore, we use the power of facial expressions as the title of this subsection and also as the title of the thesis.

To assess the power of facial expressions, we need a means to measure facial expressions. The Facial Action Coding System (FACS) (Ekman & Rosenberg, 1997) provides an excellent basis for acting as such a means, especially with modern tools for the automatic analysis of facial expressions. The remainder of this chapter is organised as follows. Section 1.3 provides a brief introduction to the Facial Action Coding System. Section 1.4 reviews computational approaches to analyse facial expressions. Section 1.5 formulates our Problem Statement (PS) and four Research Questions (RQs). Section 1.6 deals with the research methodology which guides the answering procedure of the RQs and the PS. Finally, section 1.7 provides an outline of the thesis.

1.3 THE FACIAL ACTION CODING SYSTEM

Facial expressions have been extensively studied by Paul Ekman (see, e.g., Ekman & Rosenberg, 1997). Ekman claimed that human facial expressions consist of building-blocks called facial *action units* (AUs), i.e., local changes of the facial appearance caused by the activity of facial muscles. An example of a facial action unit is the *Inner Brow Raiser*, which represents the elevation of the inner parts of the eyebrow. The Facial Action Coding System was proposed by Ekman and Friesen (1978b) in an attempt to systematically describe facial expressions in terms of action units. According to Ekman and Friesen (1978b), FACS is a comprehensive, anatomically based system for measuring all visually perceptible facial movements. Each AU has a numeric code. For instance, action unit 1 (AU1) is associated with the *Inner Brow Raiser*. Examples of action units and their meanings are given in Appendix A. Interestingly, facial expressions that are described by certain combinations of action units correspond to emotional expressions. For instance, the facial expression of *Joy* is associated with the combination of AU6 (*Cheek Raiser*) and AU12 (*Lip Corner Puller*).

For a long time the identification of action units from photographs or videos was performed by human FACS coders, but in recent years computational methods became available for the automatic coding of facial action units.

Here we would like to remark that FACS is not without its critiques. At this place, we mention two of them. First, the assumption of the existence of (six) basic emotions has been questioned by Ortony and Turner (1990). They claimed that there is no evidence for the existence of basic emotions. Second, FACS is based on the assumption that facial action units are the building blocks of facial expressions, because each of them is associated with a specific facial muscle. An alternative conception is that the building blocks of facial expression are defined in terms of information content. As a transmitter of information, facial dynamics may have evolved to maximize the efficiency of information transfer. Smith, Cottrell, Gosselin and Schyns (2005) found evidence for such efficiency.

1.4 AUTOMATIC FACIAL ACTION CODING

In what follows, three automatic facial coding systems are described: the Computer Expression Recognition Toolbox (1.4.1), Intraface (1.4.2), and Face++ (1.4.3). In this thesis, we applied the Computer Expression Recognition Toolbox and Intraface for the extraction of facial expression information from images and video sequences.

1.4.1 Computer Expression Recognition Toolbox

The Computer Expression Recognition Toolbox (CERT), is a powerful software tool for the automatic coding of facial expressions (cf. Littlewort, Whitehill, Wu, Fasel et al., 2011). Given an image or video, CERT estimates the intensity of twenty different facial action units and of seven different prototypical emotional facial expressions (i.e., the seven basic emotions identified by Ekman and Rosenberg (1997), viz. HAPPINESS, SADNESS, SURPRISE, FEAR, ANGER, DISGUST and CONTEMPT). CERT also estimates the locations of ten facial features as well as the head pose, i.e., yaw (the direction of shaking "no"), pitch (the direction of nodding "yes"), and roll (the in-plane rotation of the face). A database of posed facial *expressions* has evoked considerable research in social psychology. CERT achieves an average recognition performance of more than 90 percent on the Cohn-Kanade (CK+) database (cf. Littlewort, Whitehill, Wu, Fasel et al., 2011). On a spontaneous facial expression dataset, CERT achieves an accuracy of nearly 80 percent (cf. Littlewort, Whitehill, Wu, Fasel et al., 2011).

A video sequence of a frontal face is translated by CERT into a multivariate time-series of (amongst others) action-unit estimates. These time-series can be analysed through traditional statistics (e.g., correlation) or with modern machine learning methods (see, e.g., Biel et al., 2012).

CERT has been distributed under an academic license before it became a commercial product. Figure 1.1 illustrates the CERT application. After loading a video file, in each frame the face is detected and the action units describing the facial expressions of the detected face are analysed. The bar plots on the right show the action unit estimates. For instance, the upper left plot shows the estimates for anger one of the seven basic emotions. Each black bar represents the estimate for one frame. The horizontal axis represents time (expressed in frames), the vertical axis represents the (normalised) AU intensity. Intensities larger than zero indicate evidence for the presence of the action unit.

1.4.2 Intraface

Intraface (Xiong & Torre, 2013) is publicly available automatic facial coding software. Intraface uses a Supervised Decent Method (SDM) to estimate the locations of 49 landmarks: 2×5 landmarks representing the two eyebrows, 2×6 landmarks for the eyes, 9 landmarks for the nose, and 18 landmarks for the mouth. SDM estimates the three-dimensional head pose for each image or frame. Head pose is represented by yaw, pitch, and roll (see 1.4.1). Intraface is available as a Windows GUI, a matlab, and as mobile app[2].

1.4.3 Face++

Face++ is a cloud-based service for automatic facial coding. It is based on a deep convolutional neural network that maps a face onto estimated locations of 83 facial landmarks (Zhou, Fan, Cao, Jiang & Yin, 2013): 19 landmarks representing the lower

2 www.humansensing.cs.cmu.edu/intraface

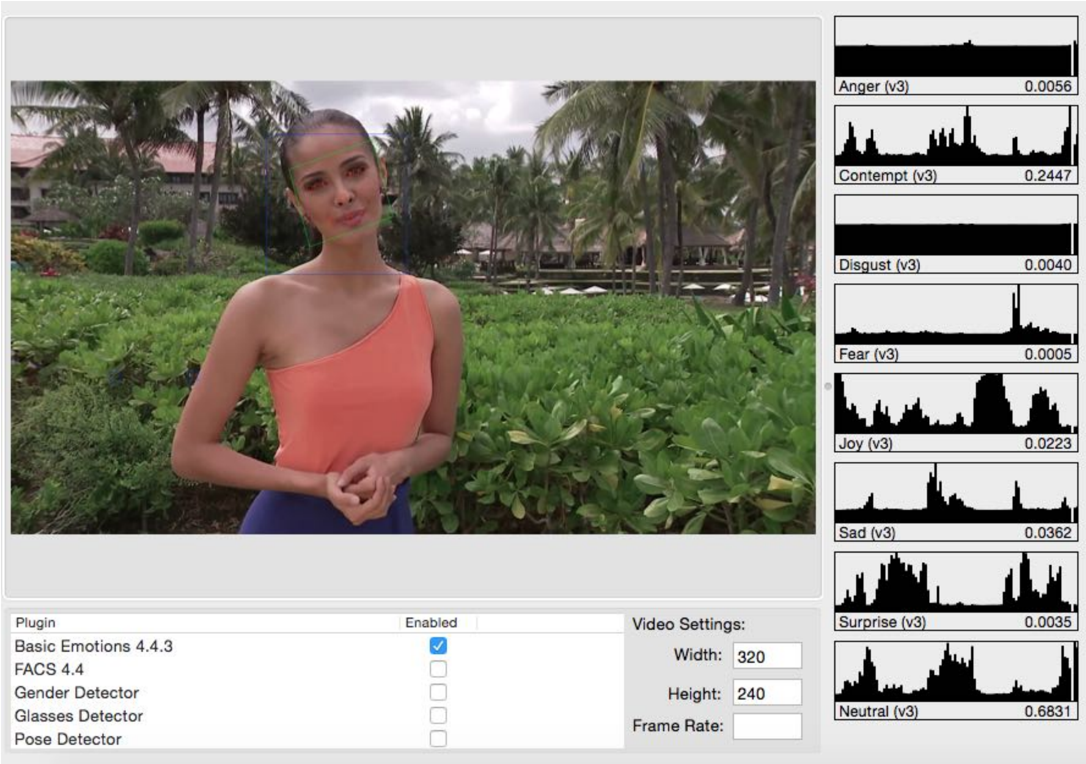

Figure 1.1: Illustration of the interface of the CERT application.

facial outline including the chin, 2×10 landmarks representing the eyes, 2×8 landmarks for the eyebrows, 18 landmarks for the mouth, and 10 landmarks for the nose. Face++ is publicly available via an API that reads images and returns a JSON file with the landmark coordinates.

1.5 PROBLEM STATEMENT AND RESEARCH QUESTIONS

The available computational tools allow us to perform objective analyses of facial expressions. In combination with the setting of the context that is assumed to constrain the display rules, we are ready to formulate our problem statement (PS).

PS: *What is the power of facial expressions in a competitive setting?*

Our research is guided by four research questions (RQs), each of which is related to one of the four competitive contexts: the female pageant contest, the male pageant contest, the music contest, and the leadership contest. Each RQ is preceded by a brief description that gives the context. The first research question deals with Miss World contestants and reads as follows.

RQ1: *To what extent do facial expressions contribute to the attractiveness ratings in relation to femininity?*

The second research question aims at discovering the contribution of facial expressions in the assessment of male beauty. In particular, the static and dynamic aspects of attractiveness will be analysed using short video segments of the male contestants. These segments represent so-called *thin slices*, which have been experimentally shown to provide sufficient information for assessing personality, affect, and interpersonal relations (cf. Ambady, Bernieri & Richeson, 2000). The second research question reads as follows.

RQ2: *To what extent do thin slices of facial expressions contribute to the attractiveness of males?*

The third research question focusses on the context of a music contest. Building on a recent study by Tsay (2013), suggesting that visual information contributes to the assessments of winning performances, our third research question focusses on facial expressions and reads as follows.

RQ3: *To what extent do facial expressions allow for the identification of winning musicians?*

Finally, the fourth research question investigates the context of a leadership contest. Using videos of leadership contestants, we attempt to assess the relationship between facial expressions and assessments of leadership qualities. The fourth research question reads as follows.

RQ4: *What is the relation of dynamic facial expressions to leadership assessment?*

The answers to these four research questions enable us to formulate an answer to the problem statement.

1.6 RESEARCH METHODOLOGY

In this study we employ a research methodology, which consists of the following six stages.

1. Reviewing and analysing the scientific literature
2. Collecting, editing and extracting facial expressions from video sequences
3. Performing traditional correlation analysis and modern prediction analysis (machine learning)
4. Performing comparative experiments
5. Analysing and interpreting the results obtained

6. Formulating conclusions.

Below, each of the six stages is briefly explained.

1. *Reviewing and analysing the scientific literature.* We review and analyse the scientific literature with three objectives. The first objective is to identify the state-of-the-art findings of relevance to the four research questions. The second objective is to identify suitable computational analysis methods from the literature. The third objective is to establish well-founded experimental set-ups for the experiments performed to answer RQ1, RQ2, RQ3, and RQ4. Appropriate literature is found in the research fields of (1) social signal processing and affective computing, (2) machine learning and data mining, (3) probability theory and statistics, and (4) nonverbal signals and facial expressions.

2. *Collecting, editing and extracting facial expressions from video sequences.* The video sequences available usually consist of raw material. From these, (a) proper slices and metadata need to be collected, (b) redundant fragments removed, and (c) relevant fragments extracted.

3. *Performing traditional correlation analysis and modern prediction analysis.* The traditional methods of statistical inference rely on tools such as correlation to determine the relation between independent variables (facial expression estimates) and the dependent variable (assessment). The modern methods use data analyses and aim at prediction.

4. *Performing comparative experiments.* Predictive analysis by means of machine learning requires a comparative evaluation of different subsets of independent variables (features) and parameter settings. Comparative experiments will be performed to determine the optimal setting of the machine learning algorithms in a suitable cross-validation setting and to determine the contribution of facial-expression components to the prediction performance.

5. *Analysing and interpreting the results obtained.* The purpose of the analysis and interpretation is threefold: (a) determining the correlations of facial expressions (AUs) with the assessment under consideration, (b) predicting the assessments, and (c) understanding and interpreting the relation between the expressions and assessments with reference to the available literature.

6. *Formulating conclusions.* Based on the results obtained when answering the four RQs, an answer to the PS can be formulated and conclusions can be drawn.

1.7 STRUCTURE OF THE THESIS

Below we provide an overview of the structure of the thesis.

Chapter 1 introduces the research topic by describing the context and by formulating the problem statement and research questions. They are investigated over the course of seven chapters. The chapter also specifies the research methodology. Table 1.1 lists

Table 1.1: Structure of the thesis.

	Chapter	PS	RQ1	RQ2	RQ3	RQ4
1:	INTRODUCTION	x	x	x	x	x
2:	DIGITAL ANALYSIS OF BEAUTIFUL FEMALE FACIAL EXPRESSIONS		x			
3:	STATIC AND DYNAMIC CUES TO MALE ATTRACTIVENESS			x		
4:	THE FACIAL EXPRESSIONS OF WINNING MUSICIANS				x	
5:	THE FACIAL EXPRESSIONS OF LEADERSHIP					x
6:	GENERAL DISCUSSION	x	x	x	x	x
7:	CONCLUSIONS AND FUTURE WORK	x	x	x	x	x

the chapter titles and indicates the involvement of the problem statement (PS) and the research questions (RQ1-4) for each chapter.

Chapter 2 deals with RQ1. Facial expressions in relation to femininity are investigated by three sets of features: facial expression features, smiling features, and emotional expression features.

Chapter 3 deals with RQ2. It handles the thin slices taken from video sequences of male pageants. Three cues of male attractiveness are investigated: symmetry, averageness, and masculinity.

Chapter 4 deals with RQ3. It investigates the influence of dynamic facial expressions in a music competition. We examine the result of an international piano competition. Performance and expressions are compared.

Chapter 5 deals with RQ4. It investigates the relation of dynamic facial expressions on the assessment of leaderships traits. We investigate a leadership competition, extract the personal traits from both a survey and collected computational data. Finally, we compare the results.

Chapter 6 gives a general discussion of the findings in relation to existing work. The emphasis is on the power of facial expressions in personal assessments in competitive contexts.

Chapter 7 provides conclusions by summarising the answer to the research questions and then answering the problem statement. In addition, the chapter points at future work.

2 DIGITAL ANALYSIS OF BEAUTIFUL FEMALE FACIAL EXPRESSIONS

In this chapter we address the dynamics of female facial expressions. The aim of the study is to provide an answer to the first research question.

RQ1: *To what extent do facial expressions contribute to attractiveness ratings in relation to femininity?*

Facial attractiveness has been studied extensively in the past decades. The majority of these studies were behavioural studies in which participants were instructed to rate the attractiveness of facial pictures. The present chapter exploits computational methods to study the digital analysis of female facial attractiveness. Our study is guided by the following research approach: (1) digitally measuring the dynamics of facial features of beautiful women contestants of the miss world competition and (2) relating these measurements to available attractiveness ratings. We expect that the approach gives us an adequate insight into the contribution of facial expressions to an attractiveness rating in relation to femininity. Therefore, the aim of this chapter is to establish the contribution of facial expressions to attractiveness in relation to femininity by means of a computational analysis of video sequences. In other words, and that is crucial for our research: do facial expressions contribute *individually* to attractiveness or are they dependent on the *level* of femininity?

The course of the chapter is organised as follows. Section 2.1 reviews three previous behavioural findings on the contribution of facial expressions to attractiveness. Section 2.2 describes the research methodology by outlining the video collection and the statistical and computational analyses. The results are presented in section 2.3. Finally, section 2.4 discusses the results and provides a conclusion and three recommendations for further research.

2.1 THREE CHARACTERISTICS OF ATTRACTIVENESS

So far, three main facial characteristics have been found to determine the assessments on human attractiveness: facial symmetry, averageness and sexual dimorphism (cf. Perrett et al., 1998; Fink, Grammer & Thornhill, 2001; Baudouin & Tiberghien, 2004). In the literature, the contribution of symmetry to attractiveness is observed for both males and females, while the contribution of averageness is found exclusively for female faces (Rhodes et al., 2011). In female faces, the contribution of symmetry to attractiveness is partly caused by averageness (Baudouin & Tiberghien, 2004). Whilst sexual dimorphism, i.e., the masculinity or femininity of the face, is probably the most powerful predictor of attractiveness (cf. Perrett et al., 1998; Rhodes, 2006). Therefore, in the current study sexual dimorphism is adopted as a measure of static attractiveness (see subsection 2.2.4). Below we briefly discuss the three characteristics. In subsection 2.1.1, we review the literature on the contribution of static versus dynamic characteristics. In subsection 2.1.2 we examine the relation between facial expression and attractiveness. In subsection 2.1.3 the facial action unit and the emotional expression are related. Finally, we give a brief overview of previous work of facial expressions and attractiveness in subsection 2.1.4.

2.1.1 Static versus Dynamic Attractiveness

Whereas traditional studies of facial attractiveness focussed on static images, i.e., photographs (cf. Maret, 1983; Dickey-Bryant, Lautenschlager, Mendoza & Abrahams, 1986; Watkins & Johnston, 2000), more recent studies address the dynamic features of attractiveness (cf. Krumhuber & Kappas, 2005; Morrison, Gralewski, Campbell & Penton-Voak, 2007; Penton-Voak & Chang, 2008). The contribution of dynamic features to attractiveness has been subject of considerable debate. First, Rubenstein (2005) suggested that static and dynamic characteristics of faces are assessed by different evaluative standards. He found that a dynamic face assessed to be highly attractive was not necessarily assessed to be attractive when presented as a still image. Then, partly supporting Rubenstein's suggestion, Lander (2008) put forward some specific results in which gender differences played a special role. Lander found medium correlations (by female raters) and large correlations (by male raters) between the attractiveness ratings of static and dynamic female faces. However, he did not find a significant correlation between static and dynamic male faces. Lander's (2008) results were confirmed by Penton-Voak and Chang (2008). In the five years thereafter, two more recent experimental findings were published. They indicate that static and dynamic attractiveness are largely identical. In 2011, Rhodes et al. (2011) reported a high agreement ($r \approx 0.83$) between attractiveness ratings for static male facial images and moving male facial images. In 2013, Kościński (2013) found that the attractiveness of static and dynamic faces did not differ irrespective of facial sex.

2.1.2 Facial Expressions and Attractiveness

The main difference between static and dynamic faces is caused by the (possible) change in facial expressions. A few studies addressed the role of facial expressions in attractiveness ratings. Morrison et al. (2007) showed that blinking, nodding, shaking, and overall movement correlate positively with attractiveness. Not surprisingly, smiling has often been found to contribute to attractiveness (cf. Kościński, 2013). Krumhuber and Kappas (2005) had found a positive relation between a dynamic smile and assessments of attractiveness. They found that when females dynamically smiled for longer periods of time, they were assessed to be more attractive than when they smiled during shorter periods of time (see also Penton-Voak & Chang, 2008). Evidently, duration of a smile is defined for dynamic faces only. It suggests that duration-of-smiling is a dynamic feature that has a unique contribution to attractiveness. This raises the following question: to what extent do facial expressions contribute to attractiveness ratings? Obviously, the question is equally relevant to static facial expressions (e.g., in relation to photographic images) as to dynamic facial expressions (e.g., in relation to video clips). Modern digital methods for the automatic coding and analysis of facial expressions offer useful tools to address these two questions.

However, the obvious fact that dynamic sequences contain more information for facial perception than static images suggests that it is worthwhile to investigate the nature of the dynamic information (Roberts et al., 2009). Moreover, as far as we know until now, the contribution of dynamic facial expressions to attractiveness has not been studied with computational methods (cf. Laurentini & Bottino, 2014). What we found is some work on computational analysis of facial expressions in static images (Whitehill & Movellan, 2008) and on the computational analysis of statics and dynamics of facial landmarks (Kalayci, Ekenel & Gunes, 2014). In what follows, we briefly report on the three examples of computational analysis, mentioned above.

First, Whitehill and Movellan (2008) performed a computational analysis of the facial action units in still images of female and male faces (the GENKI database) and found that static facial expressions (as measured in terms of facial action units) correlated with attractiveness.

Second, Kalayci et al. (2014) used machine learning to determine to what extent static and dynamic features of 48 facial landmarks contribute to facial attractiveness. They found that dynamic features do contribute to predicting facial attractiveness, but they did not consider the precise contribution of the facial expressions.

Third, Laurentini and Bottino (2014) suggested that extending computer attractiveness analysis to facial expressions as well as performing an automatic analysis of attractiveness of facial movement appear to be a new promising area.

As a conclusion we may state that the automatic analysis of facial expressions requires a formalisation of facial movements. In subsection 2.2.5 (called prediction) three machine learning experiments are described to measure the contribution of three types of facial expressions (i.e., facial action unit expressions, smiling expressions, and emotional expressions).

2.1.3 Facial Action Units and Emotional Expressions

Facial expressions are generated by contractions of facial muscles, which results in temporally deformed facial features such as eye lids, eye brows, nose, lips and skin texture (cf. Fasel & Luettin, 2003). A fine-grained description of facial expressions is needed in order to capture the subtlety of human facial expression (cf. Kanade, Cohn & Tian, 2000). As explained in chapter 1, the Facial Action Coding System (FACS) is an observation-based system of facial expressions developed by Ekman and Friesen (1978b). FACS consists of 44 so-called Action Units (AUs), which constitute the building blocks of facial expressions. Examples of AUs are the "brow raiser", the "lip tightener" and the "dimpler" (see Appendix A for an overview of AUs relevant to this study according to the output of CERT).

Well-known facial expressions are defined by specific combinations of AUs. Table 2.1 lists the AUs associated with the seven emotional expressions Happiness, Sadness, Surprise, Fear, Anger, Disgust and Contempt.

Table 2.1: List of Action Units (AUs) associated with seven emotional expressions.

Action Units (AUs)	**Emotions**
6+12	Happiness
1+4+15	Sadness
1+2+5+26	Surprise
1+2+4+5+7+20+26	Fear
4+5+7+23	Anger
9+15+16	Disgust
R12+R14	Contempt

Our computational study of the relation between facial expressions and attractiveness will rely on AUs and the seven emotional expressions as defined by FACS.

2.1.4 Previous Work on Facial Expressions and Attractiveness

Before turning to our study of attractiveness, we briefly review existing studies on the contribution of facial expressions to attractiveness, specifically in females. The most consistent finding in the literature concerns the contribution of smiling or also called facial expressions of happiness (see Tracy & Beall, 2011). Moreover, they studied the impact of emotional facial expression on sexual attraction. Using still images, they found that the expressions of happiness in female persons were the most attractive emotional expressions, whereas in males, it was rated as one of the least attractive expressions. Golle, Mast and Lobmaier (2014) found that the *intensity* of smiles influences attractiveness in static images strongly. In addition, there is some evidence that feminine motion (in dynamic facial expressions) contribute to attractiveness. Morrison et al. (2007) used dynamic animations to study attractiveness. In order to remove any shape cue, they extracted the facial landmarks from videos of real persons and used them to animate an androgynous shape-normalised face. Participants in their study were able to discern male from female animations above chance level. The amount of feminine motion was positively related to attractiveness. Possibly, because it reflects extraversion, which is an established attractive personality trait.

2.2 RESEARCH METHODOLOGY

In this section, we describe the video collection used for our computational analysis of attractiveness (2.2.1), we outline the method used to measure facial expressions from the videos (2.2.2), we discuss automatic expressions extraction (2.2.3), we perform correlation analysis (2.2.4) and we do prediction analysis (2.2.5).

2.2.1 Video Collection

The video collection used for our study contained 127 profile videos of 127 participants of the Miss World 2013 contest. They were downloaded from *YouTube* and obtained using the query "Miss World 2013 - Profile Video -" followed by the country name. Each of the video sequences contains a reasonably standardised presentation of a contestant, who presents herself by providing rather similar personal information and by motivating her reason to join the Miss World competition. Throughout the video, the contestants are facing the camera so that their expressions are clearly visible. All video sequences were encoded in the Motion Picture Experts Group Layer-4 (MPEG-4) format with a resolution of 1920×1080 pixels. The durations of videos range from 15 to 60 seconds. Figure 2.1 displays six sample frames of the videos for six contestants of the Miss World 2013 competition. We have chosen the representatives of the Philippines, the Netherlands and Indonesia, moreover three other participants of the contest, Miss Hong Kong, Zambia and Lesotho. The average scores assigned by the judges and the ranks are indicated between parentheses. For details we refer to the caption under figure 2.1.

Figure 2.1: Sample frames of six contestants of the Miss World 2013 competition. The average scores assigned by the judges and the ranks are indicated between parentheses. From left to right: Miss Philippines (4.81/1), Miss Netherlands (3.78/17), Miss Indonesia (3.77/19), Miss Hong Kong (2.33/98), Miss Zambia (1.68/125), and Miss Lesotho (1.66/126).

2.2.2 Measuring Facial Expressions

The average scores were awarded to the contestants by seven professional judges. The scores were used as measures of their attractiveness. The degree of absolute agreement of the average assessment was good (intraclass correlation $= 0.88$ (cf. McGraw & Wong, 1996)). The judges were representatives of agencies involved in the Miss World competition. They were instructed to give each contestant a score A, with a value ranging from 0 to 5. The following verbal labels were associated with these scores.

- *no chance at all* ($A < 1$)
- *not impressive* ($A < 2$)
- *nice candidate* ($2 \leqslant A < 3$)
- *very good candidate* ($3 \leqslant A < 4$)
- *extraordinary candidate* ($4 \leqslant A < 5$)

The scores awarded by the judges were retrieved from the *Miss World 2013* website[3]. Scores were available for all contestants, except for the contestant from China, which we therefore removed from the collection. Thus, our final data set consisted of a collection of 126 video sequences and the associated scores of the seven judges. The scores were averaged over the judges, yielding a single average score per contestant. Figure 2.2 shows the histogram of the average scores assigned to the contestants.

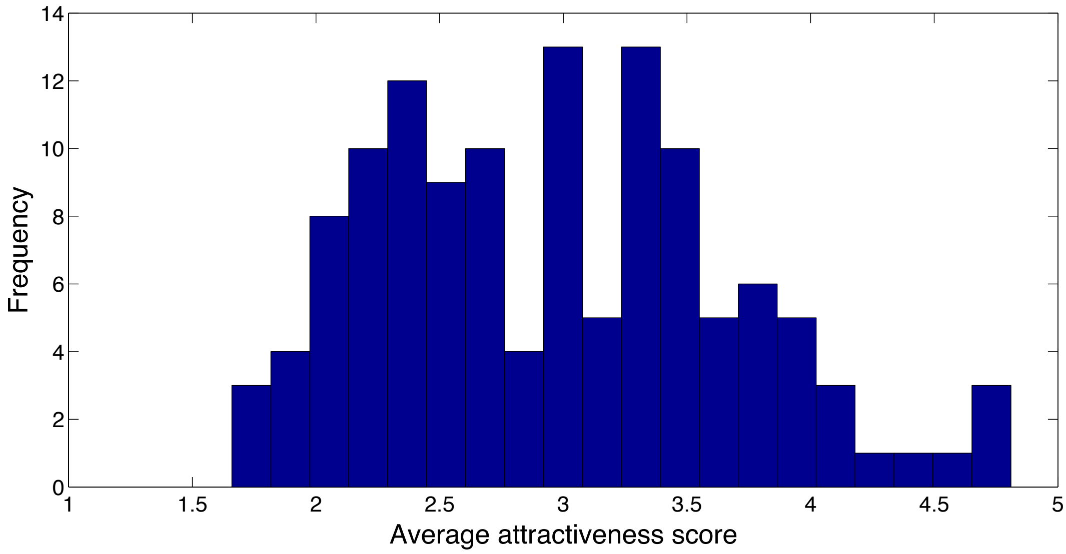

Figure 2.2: Distribution of the average attractiveness scores assigned by the 7 judges to the 126 Miss World contestants. The bin widths have been determined automatically by Matlab to cover the range of scores and to reveal the shape of the distribution.

2.2.3 Automatic Expression Extraction

Frame-based expression estimates were obtained by processing all video sequences with the Computer Expression Recognition Toolbox (CERT) (Littlewort, Whitehill, Wu, Fasel et al., 2011). For each frame, CERT generates (amongst others) estimates for three sets of facial-expression features:

- 28 facial action units
- 7 emotional expressions
- 1 smile detector output

CERT automatically codes facial action units with an accuracy of 80 to 90% (Littlewort, Whitehill, Wu, Fasel et al., 2011), depending on the quality of the video sequences and the visibility of the faces. We performed a preliminary evaluation of the accuracy of CERT on our video sequences on a random subset of video fragments. The CERT estimates agreed very well with our observation of the expressions.

3 globalbeauties.com/world/judges-scores/ (retrieved 25-9-2013)

CERT was trained on posed and spontaneous emotional expressions using weighted AU estimates obtained by training a multivariate logistic regression classifier. On the spontaneous expressions, the average recognition accuracy is almost 80%.

Whereas one of the facial action units, AU12 (Lip Corner Puller), is present in all smiles, CERT provides a separately trained smile detector. Using a subset of the 20,000 image GENKI dataset[4], the smile detector obtained a detection accuracy (2AFC) of 97.9% correct. The intensity (magnitude) of the smile detector was shown to correlate very well with human estimates of smile intensity (cf. Whitehill, Littlewort, Fasel, Bartlett & Movellan, 2009).

A frame-based estimate of the average femininity of the contestant is obtained by using the "Gender" feature of CERT. This estimator generates a positive value for female faces and a negative value for male faces. The estimator is trained on a large collection of male and female faces (Littlewort, Whitehill, Wu, Fasel et al., 2011). The magnitude of the CERT value is proportional to sexual dimorphism (Littlewort, Whitehill, Wu, Fasel et al., 2011).

The estimated values for all features were averaged per video sequence (contestant), yielding:

- 28 *average facial action unit (AU) estimates*,
- 7 *average emotional expression estimates,*
- *a single average smile estimate*, and
- *a single average femininity (AF) estimate*.

2.2.4 Correlation

To determine how individual estimates correlate with the attractiveness scores, we determined the Pearson product-moment correlation of the individual features and their attractiveness scores. The Pearson product-moment is a measure of the linear correlation (dependence) between two variables, giving a value between -1 and 1 (both inclusive), where 1 is a perfect positive correlation, 0 is no correlation, and -1 is a perfect negative correlation (cf. Stigler, 1989). A p-value is used as an indication of statistical significance. In the context of hypothesis testing, a p-value smaller than 0.05 is taken as a sign that the associated correlation is significant. This p-value means that the probability of finding a correlation where in fact there is no correlation is less than 1 out of 20. When performing multiple correlation analyses (as in our experiment), hypothesis testing dictates a corrected p-value to compensate for the elevated probability of finding a significant outcome. Our goal is to explore possible associations between facial features and attractiveness, rather than to test hypotheses. Therefore, we adhere to the p-value of 0.05 as a criterion for detecting potentially interesting facial features that are associated with attractiveness.

4 http://mplab.ucsd.edu. The MPLab GENKI Database

2.2.5 Prediction

Preliminary experiments revealed linear regression models to be insufficiently powerful to predict attractiveness scores from the features. Therefore, we resorted to more powerful nonlinear models. To assess the extent to which facial expressions support the prediction of attractiveness, we trained Random Decision Forests (RDFs) for regression (Ho, 1995; Breiman, 2001) using Matlab's R2014b TreeBagger function. The main parameter of an RDF is the number of decision trees constituting the forest. The parameter controls the complexity of the regression models induced from the data. In our experiments, the number of trees was set to $1,000$ which generated sufficiently complex models for prediction. The RDF algorithm contains a random component. Hence, we replicated each prediction experiment 100 times and averaged the prediction accuracy yielding an (average) Mean Squared Error (MSE).

As stated in subsection 2.1.2, the automatic analysis of facial expressions requires a formalisation of facial movements. By using CERT, which estimates AU intensities, we rely on formalised facial movements. To determine the contribution of three types of facial expressions (i.e., facial action unit expressions, smiling expressions, and emotional expressions), three machine learning experiments were performed. In each experiment the attractiveness was predicted using the facial expression type features in two ways: (1) separately and (2) together with the femininity feature. In all three experiments, we decided (see the introduction of subsection 2.1.2) that the prediction accuracy obtained by measuring the type of facial expressions together with sexual dimorphism should serve as a reference. In this manner we were able to determine to what extent each of the three facial-expression types contribute to the prediction performance both with and without the established static feature of femininity. To estimate the generalisation performance, we employed a Leaving-One-Out (LOO) cross validation procedure. By this procedure 126 separate training and testing runs are performed, each time with a different test set containing a single Miss World candidate, and a training set containing the remaining 125 Miss World candidates. For each run the mean squared error of the estimated and true value of A is computed. The average MSE is the estimate of the generalisation performance. As a baseline, the MSE_{mean} is computed as obtained by a classifier that predicts the mean attractiveness score for each instance. This baseline represents the prediction accuracy obtained by guessing the attractiveness of each contestant to be equal to the average attractiveness judgement score. Prediction accuracies of the RDF should exceed the baseline accuracy to be meaningful. Exceeding the "guessing" performance indicates that the model induced by the classifier supports a relation between the facial action units and attractiveness.

2.3 EXPERIMENTAL RESULTS

The results are presented in two parts: the correlation results (2.3.1), followed by the prediction results (2.3.2). In subsection 2.3.3 we assess the contribution of the facial expression features.

2.3.1 Correlation Results

The correlation results are presented in three parts. In part A, the correlation of average femininity (an established measure of static attractiveness) with attractiveness is presented. In part B, the correlations of individual facial features are presented. In the part C, the correlation results are summarised.

A: *Average femininity correlated with attractiveness*
The correlation analysis of average femininity revealed that it correlates weakly with the attractiveness judgement score ($r = .271$, $p = 0.0022$). Although the correlation is weak, this finding confirms our expectation that the relative assessment of the attractiveness of very beautiful women (Miss World contestants) do not differ from those of a random (more representative) sample of females. Also for very beautiful women, sexual dimorphism correlates with attractiveness. The scatter plot in Figure 2.3 represents each contestant as a point with two coordinates: average attractiveness score (horizontal axis) and average femininity (vertical axis). The dashed line is the best fitting regression line through the points. Although the correlation is not as strong as generally found for a random sample of females (cf. Rhodes, 2006), the correlation indicates that even within our biased sample of highly attractive females, femininity is still associated with attractiveness.

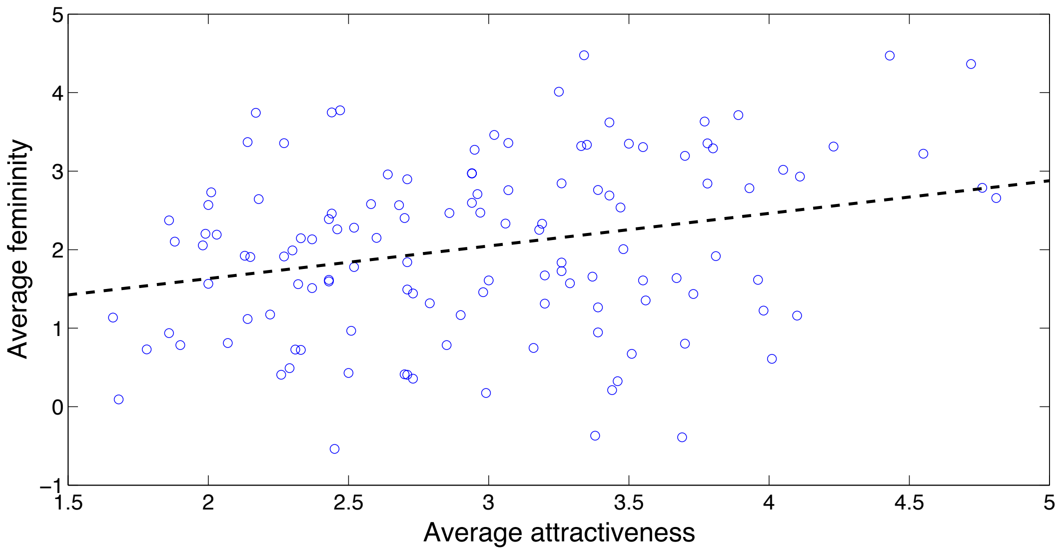

Figure 2.3: Illustration of the correlation between average attractiveness and average femininity. The dashed line represents the regression line. Each circle represents a Miss World contestant.

B: *Correlation of individual facial features*
The correlations for individual features provide a coarse indication of which elements of facial expressions (action units) may be associated with attractiveness. Table 2.2 lists the results of the correlation analysis for facial expressions. The first column specifies the facial expression feature. The second column shows the correlation value (r), and the third column lists the p-values. Entries with a p-value smaller

than 0.05 are printed in boldface. The rows in the table list the correlations for the facial expression features in three parts: (1) the facial action units (AU), (2) the smile detector, and (3) the emotional expressions. Of the facial action unit features, action units 10 (Lip Raise), 12 (Lip Corner Pull), 6 (Cheek Raise), 26 (Jaw Drop), and 28 (Lips Suck), correlate with attractiveness according to the $p < 0.05$ criterion. For the emotional expressions, the facial expression of disgust correlates negatively with attractiveness, whereas the expression of joy yields a positive correlation. These results indicate that action units associated with the lower part of the face (mouth, cheeks, jaws) correlate with attractiveness assessments and that (as to be expected) happy expressions contribute to attractiveness, whereas expressions of disgust do so in a negative manner.

C: *Summary of correlation results*
In summary, our correlation analysis revealed the following three results: (1) average femininity is weakly and positively correlated with attractiveness, (2) movements of the lower part of the face correlate positively with attractiveness, and (3) positive and negative emotional expressions correlate positively and negatively with attractiveness, respectively.

2.3.2 Prediction Results

The prediction results reflect the ability of (1) expression features and (2) their combinations to predict attractiveness ratings of previously unseen facial expressions.

Table 2.3 lists the baseline performances for the mean classifier (the classifier that always returns the average attractiveness score as a prediction) and the performance obtained by training the classifier on the average femininity score only. We found $MSE_{Mean} = 0.524$ and $MSE_{AF} = 0.532$. When a prediction error is smaller than that of the mean classifier, it acquired a model that relates facial expression cues to attractiveness. However, the prediction error for the classifier trained on average femininity only, MSE_{AF}, is larger than that of the mean classifier, indicating that, in isolation, the average femininity does not lead to meaningful predictions. Table 2.4 lists the prediction error (mean squared error) for (1) facial action units, $MSE_{ActionUnits}$; for (2) smiling, MSE_{Smile}, and for (3) emotional expressions, $MSE_{Emotional}$. The table lists the prediction errors obtained without and with the average femininity (AF) feature. By comparing the prediction results with the baseline (MSE_{mean}), we see that in the column without AF, none of the classifiers perform better than the classifier baseline. In combination with AF, the classifier trained on action units and on a smile, do outperform the baseline. The classifier trained an emotional expression is not assumed to outperform the baseline.

Figure 2.4 shows box-whisker plots representing the distribution of MSEs based on 100 replications for the different input features: Average Femininity (AF), Action Units (AUs), Smile, and Emotional Expressions (Emo). Combinations of features are represented by a + sign. The horizontal dashed line represents MSE_{mean}, the performance obtained with the mean classifier. The AUs+AF feature combination yields the best performance (lowest average MSE value). The second-best performance is

Table 2.2: Correlations (r) and associated p-values (p) of average facial expression features and attractiveness ratings. Correlations with p-values smaller than 0.05 are printed in boldface.

Expression features	r	p
AU 1 (Inner Brow Raise)	-0.134	0.14
AU 2 (Outer Brow Raise)	-0.0992	0.27
AU 4 (Brow Lower)	-0.0509	0.57
AU 5 (Eye Widen)	0.0202	0.82
AU 6 (Cheek Raise)	**0.191**	**0.032**
AU 7 (Lids Tight)	0.115	0.20
AU 9 (Nose Wrinkle)	-0.035	0.70
AU 10 (Lip Raise)	**-0.188**	**0.035**
AU 12 (Lip Corner Pull)	**0.234**	**0.0085**
AU 14 (Dimpler)	0.169	0.058
AU 15 (Lip Corner Depressor)	-0.147	0.10
AU 17 (Chin Raise)	-0.114	0.20
AU 18 (Lip Pucker)	-0.0931	0.30
AU 20 (Lip Stretch)	0.143	0.11
AU 23 (Lip Tightener)	-0.108	0.23
AU 24 (Lip Presser)	0.0193	0.83
AU 25 (Lips Part)	0.102	0.25
AU 26 (Jaw Drop)	**0.184**	**0.039**
AU 28 (Lips Suck)	**0.177**	**0.047**
AU 45 (Blink/Eye Closure)	0.104	0.25
Fear Brow (1+2+4)	0.0177	0.84
Distress Brow (1, 1+4)	-0.0916	0.31
AU 10 Left	0.0256	0.78
AU 12 Left	0.049	0.59
AU 14 Left	0.0614	0.49
AU 10 Right	-0.00383	0.97
AU 12 Right	0.0329	0.71
AU 14 Right	0.0957	0.29
Smile Detector	0.0272	0.76
Joy (Happiness)	**0.228**	**0.010**
Sad (Sadness)	-0.0755	0.40
Surprise	-0.139	0.12
Fear	0.0267	0.76
Anger	-0.0949	0.29
Disgust	**-0.183**	**0.040**
Contempt	0.0639	0.48

obtained by the AF+smile feature combination which just outperforms the mean classifier (dashed line). The AUs and AF+Emo features perform at the baseline and

Table 2.3: Baseline performances for mean classifier (MSE_{mean}) and for average femininity (MSE_{AF}).

	avg (sd)
MSE_{mean}	0.524
MSE_{AF}	0.542 (0.024)

Table 2.4: Average RDF prediction results.

	without AF	with AF
$\mathrm{MSE}_{ActionUnits}$	0.524 (0.015)	0.505 (0.023)
MSE_{Smile}	0.658 (0.015)	0.526 (0.018)
$\mathrm{MSE}_{Emotional}$	0.595 (0.024)	0.512 (0.021)

therefore do not contribute to the prediction. All other features perform worse than the baseline.

The results show that for the biased sample of very attractive women, facial expressions alone (as measured by facial action units), do not contribute to the prediction of attractiveness. Their prediction error is not lower than the prediction error obtained with the mean classifier, which acts as the guessing baseline.
Taking the comments above into consideration, we arrive at the following three results.

1. In combination with the static feature of sexual dimorphism (average femininity), facial expressions *do* contribute to the prediction of attractiveness. The prediction error is lower than the prediction error of the mean classifier.
2. Albeit to a lesser extent, also smiling expressions contribute to prediction in combination also with average femininity.
3. Emotional expressions do not contribute to prediction.

2.3.3 Contribution of Facial Expression Features

The contribution of each facial feature to the prediction can be assessed by means of a feature importance measure that is part of Matlab's R2014b TreeBagger function (Breiman, 2001). For each feature, the feature importance represents the increase in prediction error if the feature would be excluded. The higher the importance of a given feature, the larger the impact of removing that feature.

We determined the feature importance for the features in the best-performing AUs + AF feature combination, to determine the individual contribution of the constituent action units. The results are displayed in Figure 2.5, showing the features (action units and AF) with a positive feature importance. In the figure, we see the feature importances in the AUs+AF condition. The labels on the x-axis represent, from left to right, the action units (numbers 1-45), the Fear Brow (FB), Distress Brow (DB), the unilaterals on the left side of the face (10L,12L,14L), the unilaterals on the right side of the face (10R,12R,14R), and AF (Average Femininity). For each feature, the relative

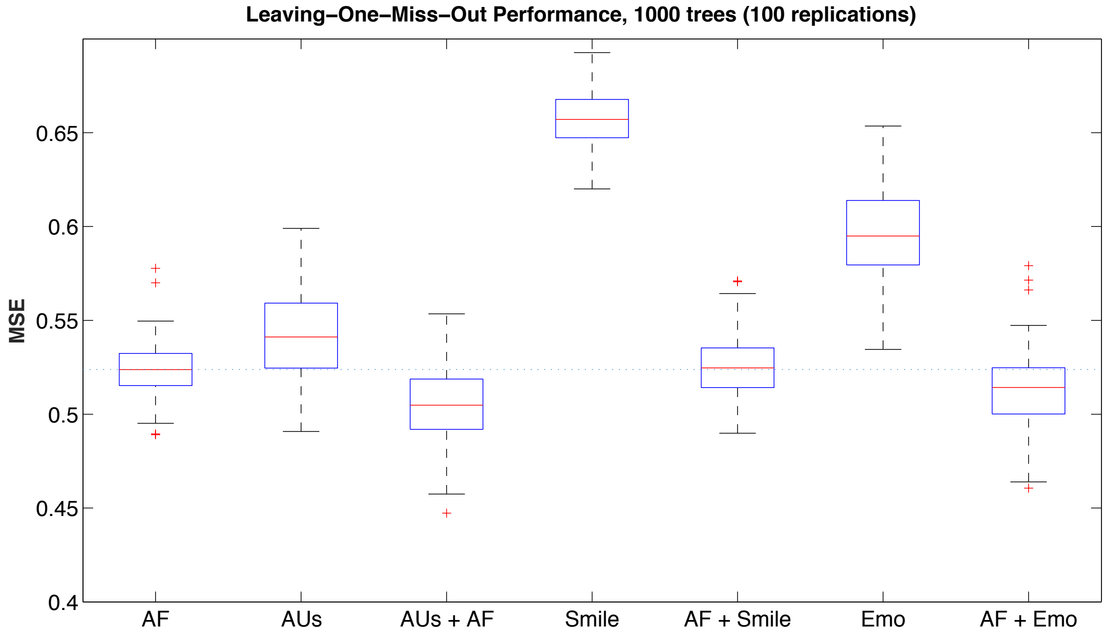

Figure 2.4: Leaving-One-Out performance (Mean Squared Error) obtained with Random Decision Forests. The box-plots represent the distributions of performances obtained for 100 replications. The input features are: Average Femininity (AF), Action Units (AUs), Smile, and Emotional Expressions (Emo). Combinations of features are represented by a + sign. The horizontal dashed line represents MSE_{mean}, the performance obtained with the mean classifier.

height of the bar indicates its relative importance for prediction, i.e., the increase in error if the feature is omitted. The most important feature is the Average Femininity (AF; outer right bar). The most important action units (AUs) in order of decreasing importance are: AU 23 (Lip Tightener), AU 28 (Lips Suck), and AU 24 (Lip Presser).

We arrive at the following two results.

1. Average Femininity is the most important feature for predicting attractiveness.
2. Dynamic facial expressions associated with the lips support the prediction of attractiveness.

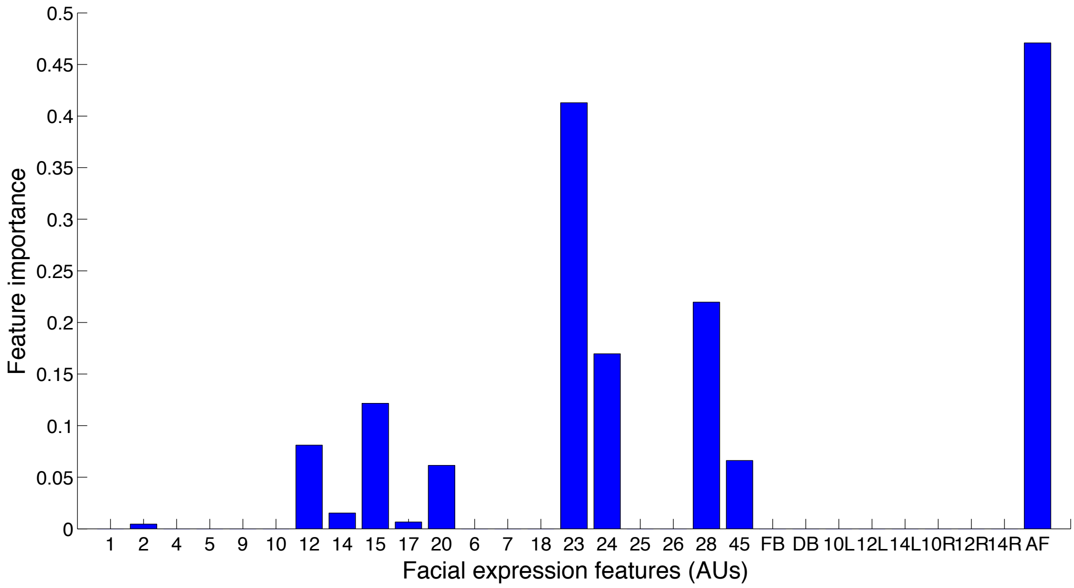

Figure 2.5: Bar plot illustrating the feature importance of the facial expression features (action units). for prediction in the AUs+AF condition. Labels on the x-axis represent action units (suffixes L and R represent unilaterals), FB = Fear Brow, DB = Distress Brow, and AF = Average Femininity.

2.4 DISCUSSIONS AND LIMITATIONS

We have performed a correlation analysis and a prediction analysis of the facial expressions of beautiful women. On the basis of the computational analysis we may conclude that when combined with sexual dimorphism, facial expressions contribute to the prediction of female facial attractiveness. Moreover, from our further observations, we may conclude that the impact of dynamic facial expressions depends on the static attractiveness as expressed by sexual dimorphism (femininity). Our discussion will consist of four parts. In 2.4.1, we compare the results of the correlation analysis with those reported on static images (cf. Whitehill & Movellan, 2008). In 2.4.2, we discuss the importance of lip-related action units. In 2.4.3, we discuss the role of smiling dynamics in attractiveness ratings. In 2.4.4, we consider three limitations of our study. We complete the chapter (in 2.4.5) by answering RQ1 and by providing three recommendations for further research.

2.4.1 Comparison Correlation Analysis with Static Images

When comparing the results of our correlation analysis to the results by Whitehill and Movellan (2008), who performed an analysis of attractive facial expressions in still images, two differences and one similarity are observed. First, Whitehill and Movellan reported significant negative correlations for action units 4 (Brow Lowerer), 9 (Nose Wrinkler), and 17 (Chin Raise). Although the correlation values we obtained for these three action units were also negative, they were associated with very low p-values. Since these action units are associated in both cases with negative expressions, it is likely that Miss World candidates are trained to suppress the activation of the constituent action units. Second, the only action unit reported by Whitehill and Movellan to contribute positively to attractiveness, was action unit 5 (Eye Widen/Upper Lid Raiser). Again, our correlation result for this action unit is also positive, but with a small p-value. Also in this case the explanation may be that the candidates are trained to suppress the associated action unit, because it may represent an explicit signal to elicit some sexual arousal in the observer (Whitehill & Movellan, 2008). Third, the similarity between our research and that by Whitehill and Movellan (2008) regards the detection of a smile. Our smile detector does not correlate to attractiveness ratings, the same holds for Whitehill and Movellan (2008). However, there was a clear difference since we trained with a dataset of dynamic faces while they trained with a data set of static faces. Our provisional conclusion is that the detection of a smile is not dependent of faces being dynamically recorded or statically recorded.

2.4.2 The Importance of Lip-related Action Units

Both the correlation and prediction analyses showed the importance of the lips in dynamic facial expressions of attractiveness. In a rather recent computational analysis of static faces, Mu (2013) found the eye and nose to have a high aesthetic relevance. The importance of the dynamics of lips may be associated with speech or with non-speech related expressions. Additional research is needed to determine the contribution of speech-related facial expressions to attractiveness.

2.4.3 Smiling, Dynamics and Attractiveness

Whereas Golle et al. (2014) found that attractiveness ratings are strongly influenced by the intensity of smiling, our results indicate a more subtle effect of smiling. This is probably due to the fact that all females in our sample are smiling. Miss World contestants may have been instructed to smile at the judges to enhance their apparent attractiveness. As a consequence, smiling may have been a weak cue for attractiveness in our sample. This is reflected in the absence of a correlation for the smile detector output with attractiveness. However, the subtle pulling of the lip corners (as measured by AU 12) does show a significant correlation with attractiveness. Also for the prediction of attractiveness, smiling combined with average femininity did contribute to the prediction of attractiveness suggesting that there is some information in the smiling behaviour of the contestants that helps to predict their attractiveness scores. Possibly, also the duration of smiling may affect attractiveness (cf. Krumhuber & Kappas, 2005).

2.4.4 Three Limitations

In what follows, we discuss three limitations of our study: (A) the biased sample of females considered, (B) the biased sample of judges considered, and (C) the measurement of facial expressions.

A: The biased sample of females considered. Obviously, Miss World contestants are not representative of the general female population. In terms of attractiveness, they populate the right tail of the female attractiveness distribution, (see, e.g., F. Chen, Xu & Zhang, 2014). As a consequence, our findings are not expected to generalise to the general female population. Any effect of facial expression on attractiveness is likely to be smaller for our biased sample of beautiful women than for a random sample of females. The average difference in attractiveness of the Miss World contestants is much smaller than the average difference in attractiveness of arbitrary women. It seems likely that specific facial expressions that affect the attractiveness ratings of very beautiful women, also affect the attractiveness of less beautiful women. However, our results suggest that the effect of facial expressions is conditional on static attractiveness as measured by sexual dimorphism. Either this conditional effect of expressions does also apply in the general case, or the effect is exclusive for very beautiful women. Computational analyses of the dynamic facial expressions of randomly selected females are needed to determine which of the two possibilities applies.

B: The biased sample of assessors involved. As stated in subsection 2.2.2, the attractiveness ratings were obtained by averaging over the ratings of seven professional assessors. Although the intraclass correlation was very good, signalling a large degree of agreement between the judges, the professional ratings may differ from those of the general population. It may be the case that the professional raters based their assessment on more than facial attractiveness only. Their attractiveness scores may reflect other factors, such as, overall impression, posture, clothing and vocal attractiveness. A study by Nguyen et al. (2012) established that female attractiveness was conveyed by multiple modalities of cues, i.e., face, dressing and/or voice as modality predictors. Hence, scores based on population votes or on non-expert judges may offer a differently biased (less biased) measure of attractiveness ratings. As a related concern, it is remarked that the demographics of the jury members (gender, country of origin, and age) may have affected the attractiveness ratings. However, scientifically measuring the impact of these biases falls in my opinion beyond our study. Yet, to give the reader an impression on the sources of the biases, we have listed three potential sources, viz. Country, Beauty Agency and Occupation of the seven judges (see table B.2 in appendix B).

C: The measurement of facial expressions. A final limitation concerns the way we measured facial expressions. The automatic coding software delivers noisy estimates for facial action units and other facial features at the level of individual frames. We have averaged these estimates over the entire video sequence. The advantage of the averaging is that it leads to robust estimates of the average presence of action units. However, the averaging may obscure facial expressions that happen at a short temporal scale.

A further important consideration concerns the validity of our measurements. Are we really measuring facial expressions? The procedure employed averages over frame-based estimates of AUs. Collectively, the AU estimates provide information about the facial appearance, because a person's expressions are tightly related to her physical appearance (see Kashyap, Tulyakov & Govindaraju, 2012). Averaging the facial appearance information over multiple frames, as we do in our experiments, may result in a better estimate of the facial expressions apart from improving the measurements of facial expressions. As such, the observed enhancement in predicting accuracy associated with facial expressions may be partly or completely attributable to facial appearance cues rather than to facial expression cues. The validity of the averaging procedure will be the subject of Chapter 4.

2.4.5 Answer to RQ1

Notwithstanding these limitations, we may answer RQ1: *To what extent do facial expressions contribute to the attractiveness ratings in relation to femininity?* The answer reads as follows. Facial expressions contribute to attractiveness ratings but only when considered in combination with sexual dimorphism (femininity). Our findings show that facial expressions, when considered in combination with femininity contribute to attractiveness. On average, facial expressions in combination with femininity contribute to attractiveness. This implies that for an individual female pageant, the combination of facial expressions and femininity makes a difference on average.

Inspired by these results, we recommend that future research should aim at the investigation of the following three research topics: (1) investigating the attractiveness ratings of males, (2) investigating the contribution of speech and lip dynamics, and (3) investigating the temporal microstructure of attractive facial expressions.

3 STATIC AND DYNAMIC CUES TO MALE ATTRACTIVENESS

Facial appearance has been claimed to be the most important component of physical attractiveness (cf. Currie & Little, 2009). Most studies on facial attractiveness have relied on attractiveness judged from photographs rather than from video clips (cf. Main, DeBruine, Little & Jones, 2010; Scott & Penton-Voak, 2011). Only a few studies combined images and video sequences as stimuli (see Rubenstein, 2005; Rhodes et al., 2011; Kościński, 2013). This chapter is a survey study. The focus is on behavioural and computational findings of static and dynamic male attractiveness. The analyses will be performed on short video sequences, so-called *thin slices*. Very brief encounters with persons have been found to allow for accurate and reliable assessments of their traits or qualities (cf. Ambady et al., 2000). Such thin-slice encounters enable human assessors to make split-second decisions on the suitability or capabilities of individuals. Our research question for this chapter reads as follows.

RQ2: *To what extent do thin slices of dynamic facial expressions contribute to the attractiveness of males?*

To answer this question, we focus on two-sub questions.

RQ2a: *To what extent do the attractiveness ratings differ for static and dynamic male faces?*

RQ2b: *What static and dynamic characteristics of male faces predict the attractiveness ratings?*

RQ2a will be addressed by means of a survey study in which participants are instructed to rate the attractiveness of images and short video sequences (thin slices) of males. RQ2b will be addressed through computational analyses of the static and dynamic stimuli used in the experiment.

The chapter is organised as follows. Section 3.1 discusses the three main visual cues of male attractiveness. Then, section 3.2 reviews previous behavioural findings on the relative contribution of static and dynamic facial information. Section 3.3 describes the research method for the survey study (addressing RQ2a) and specifies the video collection and the statistical and computational analyses. Section 3.4 provides the result of the survey study and answers RQ2a. Section 3.5 describes the research method for the computational analyses (addressing RQ2b) by describing the dataset, landmark extraction and computational procedure. In section 3.6 the results of computational study are presented and the answer to RQ2b is given. Then, section 3.7 provides a general discussion on the results. Finally, section 3.8 answers RQ2

3.1 THREE VISUAL CUES OF MALE ATTRACTIVENESS

In previous work, three visual cues to male attractiveness have been discovered: symmetry, averageness, and masculinity (for an overview of the development, see Grammer & Thornhill, 1994; Pantic & Rothkrantz, 2000; Komori, Kawamura & Ishihara, 2009). We briefly discuss each of these three cues below.

Faces that have a *horizontal symmetry* are generally rated as more attractive than those that do not (cf. Perrett et al., 1999). Symmetry may signal an individual's genetic quality in defence against parasites (Fink & Penton-Voak, 2002). Symmetry also possesses other cues to good health. Highly symmetric faces are assessed as being more attractive, healthier and more physically fit than their low-symmetry counterparts (cf. Penton-Voak et al., 2001).

The second cue is *averageness*. An average face, obtained by averaging over a number of different faces, is typically assessed to be more attractive than a non-averaged face (see Komori et al., 2009). Persons with average faces are assessed to be more healthy (see Rhodes et al., 2001). The more similar an individual face is with respect to the average face, the more attractive it becomes.

The third cue is *masculinity*. Male faces that score high on masculinity are assessed to be more attractive than those that score low on masculinity (see Grammer & Thornhill, 1994). Examples of facial traits of masculinity are large jaws and prominent eyebrows (see Folstad & Karter, 1992).

The evidence supporting these three cues in relation to attractiveness prompt us to focus on their analyses.

3.2 STATIC AND DYNAMIC CUES TO ATTRACTIVENESS

The visual cues of symmetry, averageness and masculinity can all be assessed from static images of frontal faces. Assuming that these cues are sufficient to determine the attractiveness of males, presenting participants with either images or videos of male faces is likely to result in the same attractiveness ratings. In case facial dynamics provide additional cues that affect the attractiveness in a way that differs from the static cues, this may give rise to different attractiveness ratings. In previous work, three studies focussed on the relationship between attractiveness assessments of static and dynamic faces (cf. Rubenstein, 2005; Rhodes et al., 2011; Kościński, 2013). Below, we will review these three studies. Here, we remark that the studies differ in (1) the gender of assessors (female or male) and (2) the gender of the to-be-assessed models (female or male). Our focus is on female assessors that assess the attractiveness of males. However, the static versus dynamic presentation of men to women (our case), men to men, women to men (chapter 2), and women to women seems to have similar effects for both genders. Hence, our review includes studies of males and females assessing either males or females. We are now ready for our comparison.

The first study is by Rubenstein (2005). He found a difference in the evaluation of dynamic and static images. He conducted two experiments. In the first experiment he compared the attractiveness ratings of female models (rather than male models) displayed as a static image or as a 10-second video clip. In the clip, the models read a text while maintaining a neutral expression. The static image was defined as a single frame taken from the clip. The assessors consisted of males and females. Half of the assessors were first provided with 50% of the static models and then with 50% of the thin slices. For the other half of the assessors, the order was the reversed. The average attractiveness ratings on a five-point scale for the static and dynamic stimuli differed slightly: 2.87 (SD = 0.95) and 2.94 (SD = 0.92), respectively. The correlation of the ratings assigned to the same models presented in static and dynamic format was quite low (r = 0.19), suggesting a clear difference between attractiveness assessments for both formats. In the second experiment, Rubenstein examined how ratings of the emotional expression related to attractiveness. He found that the valency of emotion is a relevant cue in the dynamic format, but it was not a stimulus in the static format. Moreover, positive emotions were strongly related to attractiveness for dynamic faces (r = 0.48), but not for static ones (r = 0.11).

The second study is by Rhodes et al. (2011). In contrast to Rubenstein (2005), Rhodes et al. (2011) found no difference in the evaluation of the attractiveness of static and dynamic faces. Their study used 10-second video sequences of males, rather than females, performing the following actions: (i) rotating the head from left to right with a neutral expression, (ii) facing the camera with a neutral expression while counting from 7 to 13, and (iii) smile. In addition, static images taken from the video showed the male face looking directly at the camera with a neutral expression. The assessors were all females. The results revealed a high correlation (r = 0.83) between the attractiveness assessments of the static and dynamic faces. The average ten-point scale ratings for the still images and videos were the same: 4.1 (SD = 1.1 and 1.2, respectively). Rhodes et al. (2011) argued that assessors were able to quickly create a robust assessment about the attractiveness from a single image only. The addition of dynamic information did not seem to contribute to the attractiveness assessments.

The third study is by Kościński (2013). He found further evidence for the indication that dynamic information does not contribute to assessments of attractiveness. He conducted an extensive experiment using images and videos of 220 (115 female and 105 male) models. The static stimuli consisted of frontal faces of male and female actors with neutral expressions. For the dynamic stimuli, the models were instructed to act as if they encountered an attractive person of the opposite sex. The length of the videos varied from about 2 to 7.5 seconds. Again, a high correlation was obtained between the attractiveness ratings for static and dynamic stimuli (r = 0.7). The average attractiveness expressed by seven-point ratings given by females were for static stimuli 2.78 (SD = 0.86) and for dynamic stimuli 3.28 (SD = 0.78). When given by males these ratings equalled 2.86 (0.26) and 3.15 (0.76).

The main point of disagreement between Rubenstein on the one hand and Rhodes and Kościnśki on the other hand concerns the correlation of attractiveness ratings for static and dynamic stimuli. Rubenstein finds a low correlation, whereas Rhodes and Kościnśki report a high correlation. The difference between the findings of Rubenstein and Rhodes may be caused by the fact that Rubenstein employed female models that were assessed by males and females, whereas Rhodes used male models assessed by female assessors. Maybe, the assessment of female models depends on the presentation model (static versus dynamic). However, if that would be the case, Kościński would have found different results for the assessment of male and female. So, in the end there is no agreement. This question can therefore be coined as an open question.

In the general case, there is less disagreement among the three studies regarding the absolute difference between the attractiveness ratings for static and dynamic faces. Rhodes et al. (2011) report no difference between the average ratings for both formats, whereas Rubenstein and Kościński find a higher rating for video sequences. In summary, there is some conflicting evidence regarding the correlation of attractiveness ratings for static and dynamic stimuli that cannot be explained by the gender of the to-be-assessed model.

Our survey study aims at determining (1) the correlation between static and dynamic male faces and (2) their absolute ratings for attractive males in the somewhat more natural setting of Mister World self-presentation videos. Subsequently, our *computational* study aims at determining (3) which type of dynamic information in the facial stimuli predicts the attractiveness ratings (cf. Xiong & Torre, 2013). To this end we analyse the dynamics of the landmark configurations. In addition, we examine the dynamics of head pose in terms of the dynamic cues: yaw, pitch and roll.

3.3 RESEARCH METHOD SURVEY STUDY

This section describes the methods used for performing the survey study (addressing RQ2a). The survey study has a between-subjects design in which the two formats of facial stimuli are counter-balanced. Attractiveness ratings for the static and dynamic stimuli were collected via an online survey.

Below, we describe (A) the participants (who act as assessor), (B) the stimuli, and (C) the experimental procedure.

A: *Participants*

Female participants were invited to participate in the survey study through a message distributed via social media. In total, 365 participants accepted the invitation (average age = 21.3 years, SD = 4.20). They were assigned to one of two counter-balanced versions of the survey (see procedure under C). Version 1 was completed by 93 respondents and version 2 by 102 respondents. The remaining participants (170 in total) either did not complete the survey or were males. In passing we remark that the use of social media for surveys has its limitations. For instance, the low participation rate and volunteer bias could have affected the outcome of the survey (cf. Fenner et al., 2012). A more important observation is that the time spent to assess static pictures is (usually)less than the time spent to assess dynamic pictures (i.e., 2 minutes on average for assessing static images versus 10 minutes on average for dynamic images).

B: *Static and Dynamic Stimuli*

The stimuli for the experiment (i.e., the video collection and the picture selection) were obtained from *www.youtube.com*. In total 46 profile videos were obtained of *Mister World pageant 2014* contestants. The dynamic stimuli consisted of the initial 10

Figure 3.1: Sample frames of six contestants of the Mister World 2014 competition. From left to right: Mister Denmark, Mister Nigeria, Mister Curacao, Mister India, Mister Netherlands, and Mister Ukraine.

seconds of the video, corresponding to 300 frames per video. These short sequences contain reasonably standardised presentations of the contestants, who present themselves by providing some personal information and by motivating their reason to join the Mister World competition. Throughout the video, the contestants were facing the camera. The static images were defined as single frames of the videos showing the contestants in a representative and neutral pose. Figure 3.1 shows six examples of such images.

C: *Procedure*
The experimental procedure consisted of two versions. Version 1 dealt with the static stimuli corresponding to the first half of the alphabetically ordered Mr World contestants followed by the dynamic stimuli for the remaining contestants. For version 2, the dynamic stimuli of the first half were followed by the static stimuli of the second half. In this way, each contestant was rated on the basis of his image and of his video and each participant saw for each contestant either his image or his video (see table 3.1)

Participants were instructed to rate the attractiveness of the candidates on a 7-point Likert scale ranging from *very unattractive* (1) to *very attractive* (7). All stimuli were presented on single pages. After rating a stimulus, participants could scroll back to previous pages (stimuli and ratings).

3.4 RESULTS OF THE SURVEY STUDY

Below we present the results of the survey study. Table 3.2 lists for each contestant the average ratings and standard deviations for the static and dynamic stimuli. In addition, the difference scores (static minus dynamic rating) are listed in the last column. The attractiveness ratings (third column) are ordered according to descending attractiveness of the static images. From left to right, the columns in the table represent the following: the rank of the attractiveness rating for static images (No.), the name of the country of origin of the male pageant (Countries), the average and standard deviation of the attractiveness score for the static image (Static Images and SD), and the average and standard deviation of the attractiveness scores for the dynamic

Table 3.1: Number and version of static and dynamic stimulus assessed by participants.

Stimulus number	1-23	24-46
Version 1	static	dynamic
Version 2	dynamic	static

images (Dynamic Images and SD). The final column lists the difference scores (i.e., attractiveness score for static image minus attractiveness score for dynamic image).

From the table, we make two observations. First, the attractiveness score for the static and dynamic images are quite similar. Second, the difference scores are predominantly negative, indicating higher attractiveness score for dynamic images.

To support these observations, we computed the correlation between the attractiveness scores for the static and dynamic images and computed the histogram for the difference scores.

The correlation between the average ratings for the static and dynamic stimuli was very high: $r = 0.93, N = 46, p < 0.001$. The left part of figure 3.2 plots the average static ratings against the dynamic ratings. Each point corresponds to a Mr World contestant. The solid line is the best fitting regression line. Figure 3.3 shows the distribution of difference scores (cf. Table 3.2). A clear bias towards negative scores is visible indicating higher ratings for dynamic stimuli than for their static counterparts. The average difference score is equal to 0.40 (SD = 0.25).

Answer to RQ2a

These results allow us to answer RQ2a (To what extent do attractiveness ratings differ for static and dynamic male faces?). Our findings revealed that the attractiveness ratings of male faces in static or dynamic form are highly correlated. This indicates that the relative attractiveness of male faces is barely affected by presentation mode. However, the attractiveness ratings do differ in an absolute sense. Male dynamic faces are assessed to be slightly more attractive than their static counterparts.

Table 3.2: Attractiveness ratings of static images and dynamic images.

No.	Countries	Static Images	SD	Dynamic Images	SD	Difference
1	Netherlands	5.75	1.15	5.83	1.19	-0.08
2	Mexico	5.27	1.25	5.88	0.97	-0.61
3	Brazil	4.94	1.37	5.07	1.28	-0.13
4	Argentine	4.53	1.49	4.96	1.24	-0.43
5	Spain	4.49	1.46	4.81	1.43	-0.32
6	Italy	4.37	1.75	4.11	1.83	0.26
7	Australia	4.32	1.69	5.13	1.31	-0.8
8	Austria	4.15	1.56	4.19	1.52	-0.04
9	Denmark	4.03	1.67	4.42	1.63	-0.39
10	Bahamas	3.91	1.56	3.71	1.45	0.21
11	Russia	3.9	1.52	4.66	1.45	-0.75
12	Philipines	3.32	1.49	3.84	1.45	-0.52
13	France	3.13	1.44	3.51	1.51	-0.38
14	South Africa	3.08	1.39	3.35	1.53	-0.28
15	N. Ireland	3.06	1.61	3.11	1.57	-0.04
16	Romania	2.91	1.39	2.48	1.25	0.43
17	Peru	2.9	1.37	3.61	1.48	-0.7
18	Colombia	2.89	1.50	3.2	1.41	-0.3
19	Ireland	2.87	1.53	3.39	1.64	-0.52
20	Puerto Rico	2.86	1.23	2.92	1.43	-0.06
21	Lebanon	2.85	1.32	3.26	1.26	-0.42
22	England	2.82	1.33	3.75	1.37	-0.94
23	Malta	2.76	1.28	3.53	1.45	-0.77
24	Poland	2.73	1.42	3.12	1.39	-0.39
25	Ghana	2.69	1.52	3.1	1.85	-0.41
26	Turkey	2.67	1.40	2.46	1.53	0.21
27	Ukraine	2.47	1.32	2.44	1.32	0.03
28	Bolivia	2.39	1.20	2.54	1.22	-0.15
29	Latvia	2.31	1.34	2.46	1.18	-0.15
30	Curacao	2.27	1.45	2.25	1.28	0.02
31	Moldova	2.26	1.04	2.54	1.23	-0.28
32	Nigeria	2.26	1.32	1.83	1.14	0.42
33	Paraguay	2.16	1.14	2.48	1.31	-0.32
34	Swaziland	2.03	1.18	1.81	1.03	0.22
35	Switzerland	1.97	1.19	1.87	1.17	0.1
36	Germany	1.91	0.95	2.27	1.33	-0.36
37	Srilanka	1.86	0.90	2.29	1.22	-0.43
38	Venezuela	1.86	1.04	1.84	0.98	0.02
39	Canada	1.86	1.03	2.29	1.17	-0.43
40	China	1.74	1.01	2.1	1.12	-0.36
41	Guadalupe	1.58	0.85	1.99	1.12	-0.41
42	Wales	1.53	0.93	1.76	1.02	-0.24
43	Japan	1.3	0.60	1.45	0.73	-0.15
44	India	1.28	0.63	1.7	0.96	-0.42
45	Korea	1.2	0.52	1.47	0.69	-0.27
46	Dominican R	1.12	0.39	1.43	0.81	-0.31

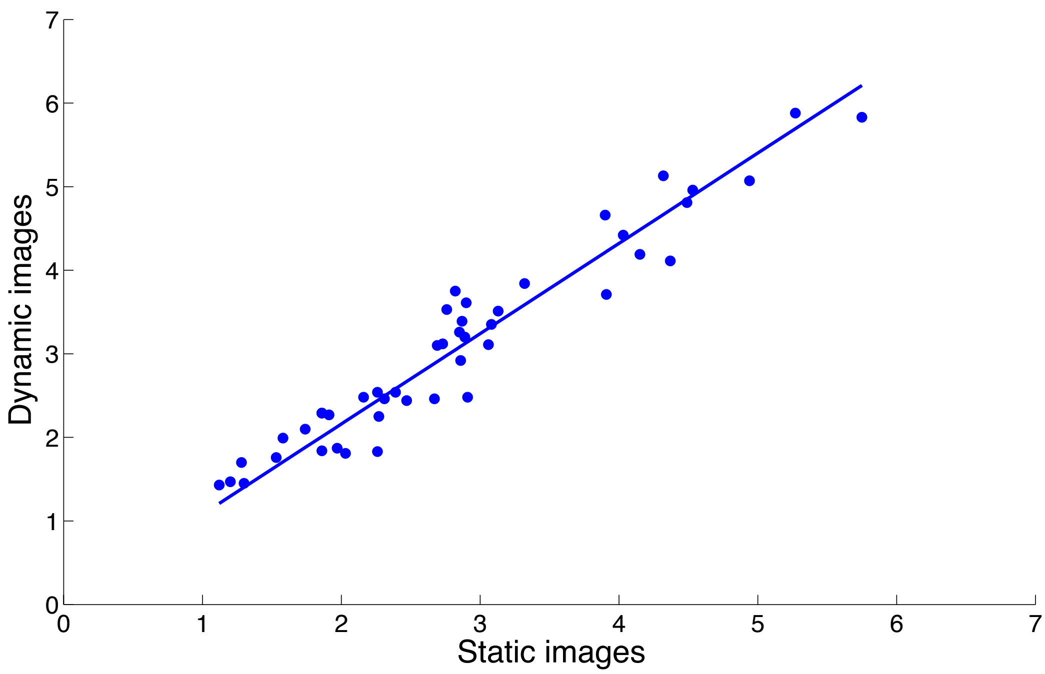

Figure 3.2: Regression analysis of static images and dynamic images.

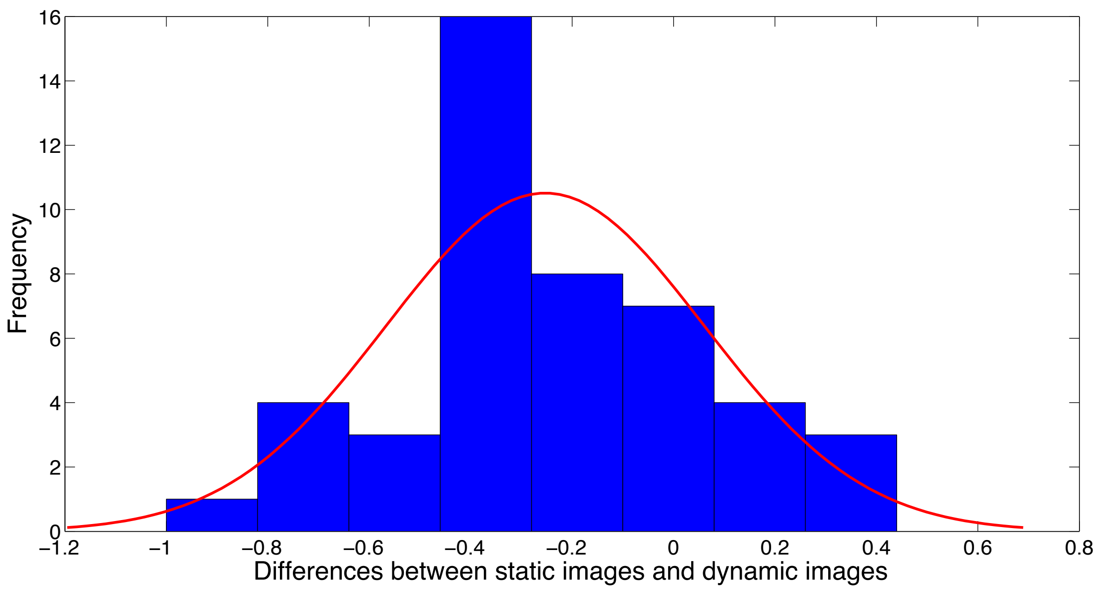

Figure 3.3: Frequency distribution of differences between static images and dynamic images.

3.5 RESEARCH METHOD COMPUTATIONAL STUDY

This section describes the research method used for performing the computational study (addressing RQ2b). The computational analysis of attractiveness is performed on facial expressions as extracted with Intraface (Xiong & Torre, 2013) from still images and video sequences. The facial landmarks correspond to fiducial points situated on the face, i.e., facial locations at or near to the mouth, nose, and eyes. In what follows we describe (A) the dataset, (B) the landmark extraction, and (C) the computational procedure used for analysing the data.

A: *Dataset*
The computational analysis was performed on the same static and dynamic stimuli as used in the study of behavioural findings.

B: *Landmark Extraction*
In order to be able to perform computational measurements of symmetry and averageness, the facial landmarks were extracted from the images and videos using the Supervised Descent Method (SDM) (Xiong & Torre, 2013) which is part of the publicly available Intraface software. SDM takes an image or video frame as input and returns estimates of the locations of 49 landmarks: 2×5 landmarks representing the two eyebrows, 2×6 landmarks for the eyes, 9 landmarks for the nose, and 18 landmarks for the mouth. As can be seen in figure 3.4 extracted landmarks are shown together with their estimates. In addition, SDM estimates the three-dimensional head pose for each image or frame. Head pose is represented by yaw (the direction of shaking "no"), pitch (the direction of nodding "yes"), and roll (the in-plane rotation of the face). All landmarks were normalised in position, scale and orientation. Position normalisation was obtained by defining the landmark at the tip of the nose (landmark 17) as the origin. All landmark configurations were rescaled to have the same distance between the centres of the two eyes. Finally, using the roll pose estimate, the landmark configurations were rotated to the upright position.

C: *Computational Procedure*
In the computational procedure we distinguish measuring static visual cues (three), and dynamic visual cues (one: the dynamics of the landmarks). To measure the three static visual cues to attractiveness, viz. (1) symmetry, (2) averageness, and (3) masculinity, the following computational procedures were used.

Symmetry (static). Facial symmetry was determined by comparing the landmarks at the left and right sides of the face. More specifically, symmetry was defined as the difference between the average distance of the landmarks on the left side of the face to the vertical midline and the average distance of the landmarks on the right side of the face to the vertical midline.

Averageness (static). For the normalised landmark configurations obtained from the still images, an average configuration was computed in which each landmark was assigned the location of that landmark averaged over all contestants. The distance

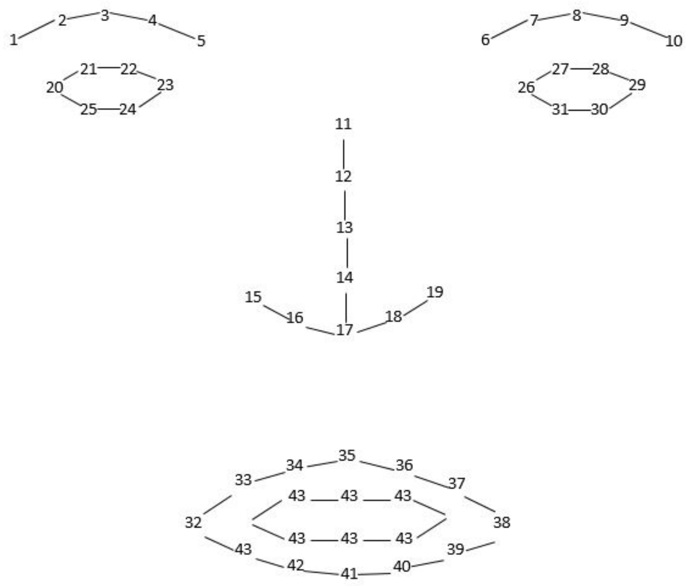

Figure 3.4: Illustration of the landmark-representation of a face. The numbers represent the landmarks. The line segments have been added to enhance visibility.

of each landmark configuration to the average (the mean Euclidean distance of each landmark to its average) was defined as a measure of averageness.

Masculinity (static). Finally, masculinity was measured by means of the "Gender" detector of CERT (Littlewort, Whitehill, Wu, Butko et al., 2011). For each image or frame of the video, this detector returns a real number with the magnitude indicating the degree of femininity if positive and the degree of masculinity if negative.

To measure the dynamic visual cues, viz. the dynamic landmark, the following computational procedure was used.

Landmarks (dynamic). To assess the contribution of the dynamics of the landmark to the attractiveness ratings, the following procedure was used. For each frame in the video, the distance of a landmark to its initial position was computed. For all but one landmark, the resulting distance vector represents the dynamic movements during the 10-second period of the video. Only for landmark 17 (tip of the nose) which is fixed at the origin, the distance vector contains all zeros. We defined the standard deviation of the individual landmark distance vectors as a measure of the temporal variation of the landmarks.

For the static and dynamic measurements we computed the correlation values of their measurement values with the corresponding average attractiveness ratings. Significant correlations indicate that information about the measurement may be of relevance to the perceived attractiveness.

3.6 RESULTS OF THE COMPUTATIONAL STUDY

Below we present the results, of the computational study. Figure 3.5 summarises the results of extracting the landmarks from the videos of the 48 contestants. Each pane shows the 49 landmark positions for the 300 frames superimposed. The amount of movement and orientation of the face and the components of a contestant is reflected in each pane. For instance, the plot of the contestant from the Netherlands reveals that he remained relatively stable with his face in a vertical position. In contrast, the contestant from Northern Ireland moved his eyebrows (they are detached from the eyes) and had his face in a tilted orientation.

The results obtained for the measurements of the static cues to attractiveness, viz. symmetry, averageness, and masculinity, are listed in Table 3.3. Only results with a p-value smaller than 0.05 are shown. The static measurements of symmetry, averageness, and masculinity correlate significantly with the attractiveness ratings given to the still images. Masculinity has the largest correlation of -0.39. The negative sign is due to the negative value of the CERT variable for males. For the dynamic ratings, symmetry is not significantly correlated with attractiveness, but averageness (0.30) and masculinity (-0.40) are.

Table 3.3: Mean correlation of static measurements with male attractiveness ratings for images and videos.

Features	Static		Dynamic	
	C	p	C	p
Symmetry (Landmarks 3-8)	0.33	0.027	-	-
Averageness	0.32	0.032	0.30	0.042
Masculinity	-0.39	0.0072	-0.40	0.0054

For the dynamic measurements, Table 3.4 lists the landmarks with significant correlations. As can be seen in the figure 3.4, all landmarks listed correspond to the mouth region. Their dynamics are, of course, highly correlated. A reason is that they reflect a single underlying factor: the mouth dynamics. Given that the signs are negative, these values indicate that attractiveness correlates negatively with mouth movements.

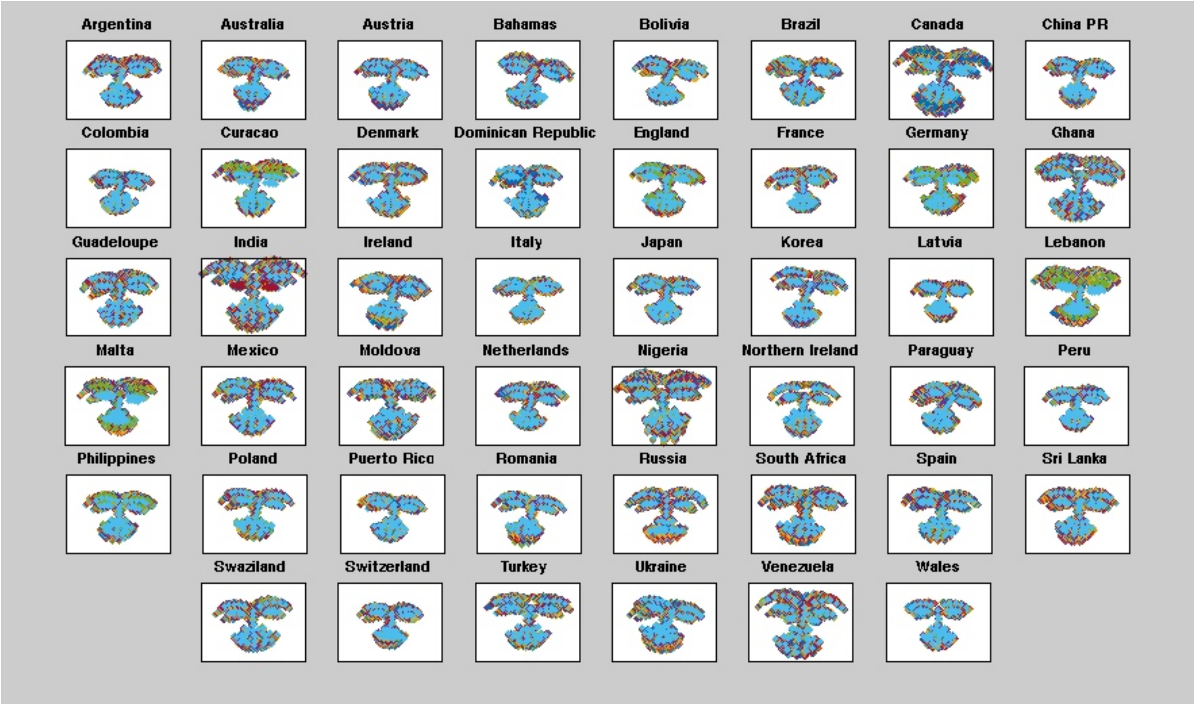

Figure 3.5: Summary of the landmark extraction from the videos of the Mr World 2014 contestants. Each pane shows the locations of the landmarks for 300 frames superimposed.

Table 3.4: Mean correlation of dynamic measurements with male attractiveness ratings for videos.

Landmark	C	p
48	-0.37	0.011
49	-0.36	0.015
47	-0.35	0.017
42	-0.33	0.027
40	-0.32	0.028
41	-0.32	0.030
39	-0.30	0.041
43	-0.29	0.047

Answer to RQ2b

The findings described above lead to the following answer to RQ2b (what static and dynamic characteristics of male faces predict the attractiveness ratings?). Our results show that the static characteristics of symmetry, averageness, and masculinity correlate with attractiveness ratings. The same is true for their dynamic counterparts, except for symmetry (for which no results could be obtained). In addition, for the dynamic measurements the movements of the mouth correlate negatively with attractiveness.

3.7 GENERAL DISCUSSION

In this chapter we examined the contribution of three visual cues to attractiveness (horizontal symmetry, averageness, and masculinity) in static (photographs) and dynamic (video) stimuli. The results of the survey study are largely in agreement with those by Rhodes et al. (2011) and Kościński (2013) in two respects. First, we find a large correlation between the assessment of static and dynamic stimuli ($r = 0.93$). Similarly, (Rhodes et al., 2011) and (Kościński, 2013) found correlations of $r = 0.83$ and $r = 0.7$, respectively. Despite the agreement in correlation, we still found the highest correlation. The reason that the correlation in our experiment was higher may be due to the fact that our static stimuli were extracted from the video sequences. Hence, the static images are contained in the dynamic sequences. This was not the case in the Rhodes et al. (2011) and Kościński (2013) studies, which may have resulted in relatively lower correlation values. The second similarity concerns the absolute differences between the attractiveness ratings of static and dynamic stimuli. Similar to Rhodes et al. (2011) and Kościński (2013), we find higher ratings for the attractiveness ratings for videos as compared to still images. This adds to the evidence that all individuals are considered to be more attractive when viewed on a video than when seen on a picture. The disagreement of our results with those by Rubenstein (2005) may be partly attributable to the fact that he used female faces as stimuli, whereas we used male faces as stimuli. Here, we remark that the contribution of facial dynamics to attractiveness has been found to be different for male and female stimuli (see Morrison et al., 2007). Repeating our study with female stimuli may help to determine whether the correlation between static and dynamic stimuli is specific to the use of male stimuli.

If the participants in our survey study relied on the three visual cues to assess attractiveness, then a computational analysis of these cues should result in similar outcomes for static and dynamic stimuli. However, our results show some little differences for averageness and masculinity (see Table 3.3). The correlations for the static and dynamic faces are about the same. This outcome supports the idea that the assessors in the experimental study relied on averageness and masculinity as cues to the assessment of attractiveness. For symmetry, no significant results were obtained which may be due to disruptions in the symmetry calculations due to head pose variations.

At the end of this discussion, we remark that we studied the effect of landmark dynamics on attractiveness ratings. We found that mouth movements (as measured by standard deviation) contribute negatively to attractiveness. The eight landmarks listed in Table 3.4 (and ordered by their p-value) all belong to the mouth region. Hence, their dynamics are highly correlated and, as a consequence, their correlations (C) with the according attractiveness ratings are all quite similar (ranging from -0.37 to 0.29). Post-hoc visual inspection of the videos revealed that the lower-ranked contestants tend to make prominent movements with their mouths during speech, while the front-ranked contestants made more subtle mouth movements while talking. A recent study of the facial dynamics of males and females revealed a specific temporal mouth movement pattern in females, but not in males (cf. Racca, Magnusson, Ades & Baudoin, 2016). This suggests that prominent movements are rather typical for males. The observation may give rise to lower attractiveness ratings.

3.8 ANSWER TO RQ2

The results of the survey study have allowed us to answer the two research questions RQ2a and RQ2b (see 3.4 and 3.6). Here, we repeat the main research question that guided our research in this chapter. RQ2: *To what extent do thin slices of dynamic facial expressions contribute to the attractiveness of males?*

The answer to RQ2 is as follows. Thin slices of dynamical facial expressions contribute to the attractiveness of males in two ways: (1) in a positive way and (2) in a negative way.

The positive contribution is that, on average, presenting a male face in a dynamic way leads to a slight increase in attractiveness rating (0.25 point on a 7-point scale). The negative contribution is that, on average, mouth movements correlate negatively with attractiveness ratings.

These answers may be translated into two recommendations for male pageants: (1) they should present themselves as much as possible in a dynamic fashion (i.e., through video or live appearances), and (2) they should restrict their mouth movements as much as possible.

4 THE FACIAL EXPRESSIONS OF WINNING MUSICIANS

Facial expressions have been investigated in domains as diverse as neuroscience, health science, and music science. For neuroscience, dynamic facial expressions transmit an evolving hierarchy of biologically information that evolves over time (Jack, Garrod & Schyns, 2014). For health studies, facial expressions can signal pain and pleasure (cf. C. Chen et al., 2016) and such be seen as efficient transmitter of health-related information (see Smith et al., 2005). For music science, facial expressions of artists displayed in videos can convey emotions accompanying or strengthening the musical experience (cf. Kavalakis, Vidakis & Triantafyllidis, 2016). The latter study lead us to review further relations between facial expressions and music.

According to professional musicians, sound is the most important information in the evaluation of music (Tsay, 2013). This seems to be an obvious statement. After all, music is mainly created for the auditory modality. Still, there is scientific evidence indicating that the *visual* modality plays an important role and, in some circumstances, even a decisive role in the assessment of the music produced. For instance, it has been established that the expressive manner in which a musical performance is executed can be more reliably inferred from the visual modality than from the auditory modality (cf. Davidson, 1993).

Apparently, vision contributes to the perception of music. This was also found by Vines, Krumhansl, Wanderley and Levitin (2006) who investigated the audiovisual perception of the musical performances of clarinet players. Participants of their experiment were presented performances of clarinetists and were instructed to rate continuously the phrasing (a measure of musical structure) and the tension (a measure of emotional response) by means of a sliding potentiometer. The experiment was performed under three distinct conditions: (i) audio-only, (ii) visual-only, and (iii) audiovisual. The results suggested that visual information served both to augment and to reduce the experience of tension at different points in the musical performance. In addition, visual information extended the sense of phrasing by cuing the beginning of new phrases, to indicate musical interpretation, and to anticipate changes in emotional content. Vines et al. (2006) claimed that the joint experience of sound and vision led to the perception of an emergent quality of the musical performance.

Although it is very common to listen and appreciate music by audio-only, e.g., through radio, CD players, or music streaming services, Vines et al.'s findings illustrate that the visual modality appears to enrich the auditory experience. That may explain the popularity of live or video performances of musicians. By watching how the musicians perform, the musical experience is enriched. This has been found to hold for a large variety of musicians, ranging from marimba players where the body movements contribute to the perception of expressiveness of the music (cf. Broughton & Stevens, 2009) to pianists whose head and shoulder movements reveal musical expression (cf. M. R. Thompson & Luck, 2012).

It seems likely that musicians also use their facial expressions, consciously or unconsciously, as a means to display or communicate messages related to their musical performance. It is nowadays well known that facial expressions play a pivotal role in the transmission of social signals (cf. Vinciarelli, Pantic & Bourlard, 2009). In what follows, we describe three studies that attempted to establish a relation between facial expressions and musical performance.

First, di Carlo and Guaitella (2004) conducted an experiment dealing with recognition of emotion in speech and in singing. The participants were asked (1) to assess a professional singer's vocal and facial emotional expressions and (2) to determine how an audience would decode those emotions. The singer's performances were presented either in audio-only, visual-only, or audiovisual format. The results showed that facial expressions play a more important role in conveying emotional information than vocal expressions. When vocal and facial expression were combined in the audiovisual format, the recognition of emotions improved slightly for speech but not for singing.

Second, W. F. Thompson and Russo (2007) attempted to determine whether the facial expressions and head movements of singers can be "read" by viewers. Three professionally trained vocalists were recorded while singing ascending melodic intervals. The experimental participants were presented muted visual recordings and were asked to estimate the sizes of the intervals that the vocalists were singing. An analysis of the estimates revealed that the participants were able to estimate interval sizes quite well on the basis of facial expressions and head movements. It turned out that the movements of the mouth, eyebrows, and head were strongly correlated with interval size. This study clearly indicates that the face transmits signals that are related to the melodic structure of the musical performance (see also the study by Davidson (2012) on the bodily and facial expressions of the internationally celebrated pianist Lang Lang).

The third and probably most compelling example is owing to Tsay (2013), who showed that listeners seem to rely more on visual cues than on auditory cues in a musical performance. In her study, she asked participants to identify the winner or who they thought should be the winner of the finalists in prestigious international classical music competitions. Tsay focussed in her study on evaluating a winner or a set of the winner (with the maximum of three), she never ranked the outcomes of the finalists into a range 1, 2, and 3. The videos showed the performances of triplets of musicians, i.e., the top-3 finalists of a single competition, in two main conditions: audio-only (no video) and visual-only (no sound). The videos showed mainly the face and upper part of the body of the musicians. Participants were instructed to identify the winner from the three presented performances. Random guessing the winner would lead to a percentage of 33 % correct (chance level). Not surprisingly, in the audio-only condition, participants performed above chance. The surprising result was that in the visual-only conditions participants also did perform above chance. Apparently, the visual signals transmitted by the face (and upper body) provided information as who would be the winner of each triplet.

The picture that emerges from these examples is that nonverbal visual signals offer information about the musical expression and even about the musical quality (as determined by winning a competition) of the performing musicians. Facial expressions seem to play an important role and are, at least partially, responsible for the ability of participants to perform better than chance on determining the winning musician. This raises the question if the performances of the participants in the study by Tsay (2013) can also be performed by a computer using the automatic analysis and classification of facial expressions. Hence, the research question addressed in this chapter reads as follows.

RQ3: To what extent do facial expressions allow for the identification of winning musicians?

To answer this research question, we collected video sequences of triplets of pianists participating in the finals of international piano competitions. We determined the contribution of facial expressions by means of automatic coding software and machine learning methods. The aim is twofold: (1) to determine whether the automatic analysis and classification yields an above-chance level of prediction comparable to human performance, and (2) to identify the relative contribution of facial cues to the prediction.

Since our study is largely based on and inspired by Tsay's experiments, section 4.1 gives a detailed description of her experiments and results. In section 4.2 our experimental set-up is outlined. Then, in section 4.3 the results are presented. Section 4.4 discusses the results and section 4.5 answers RQ3.

4.1 TSAY'S EXPERIMENTS

Tsay (2013) conducted a range of experiments to determine whether people depend primarily on auditory or on visual information when making assessments about musical performances.[5] In her experiments, Tsay used 6-second thin slices of videos from the three finalists ("triplets") of 10 international competitions (7 piano competitions and 3 violin competitions). Tsay presented the 30 thin slices in one of two or even one of three formats: (1) audio-only, (2) visual-only (i.e., silent video). In some experiments she presented 30 thin slices in one of three formats, the third being (3) audiovisual.

Below we explain Tsay's experiments with participants who were musical novices (subsection 4.1.1) and those with participants who were musical experts (subsection 4.1.2). The dominance of visual-only information is discussed in subsection 4.1.3.

4.1.1 A Novice's Assessment

The assessments by novices were studied in two experiments, which we will refer to as experiments NV1 and NV2. In Tsay's experiment NV1, 106 participants with "little to no experience in classical music" (Tsay, 2013, p.14584) were provided with one triplet for each of the 10 competitions. Each triplet consisted of three thin slices, each of which showed one of the three finalists of a single competition. The participants

5 We are indebted to Dr. Chia-Jung Tsay of the University College London School of Management for her help in the data collection supporting the experiments reported in this study.

were instructed to identify for each triplet the finalist who would win the competition. When participants were asked which presentation format they preferred, 83.3% stated that they preferred a format that included audio (i.e., (1) audio-only (2) visual-only together with audiovisual). This preference reflects the general assumption that sound is the preferred modality to identify the quality of a musical performance.

In experiment NV1, Tsay presented thin slices in two different formats (audio-only and visual-only). She found that participants were significantly more likely to identify the winners when they were presented thin slices in the visual-only format than in the audio-only format. When visual-only thin slices were presented, participants were able to identify the winning musician in 52.5% of the cases (as compared to 33.3 % chance level). Interestingly, when sound-only thin slices were presented, the performance was only 25.0 %, i.e., well below chance level.

In experiment NV2, Tsay included the third presentation format (audiovisual). The results for the audio-only and visual-only conditions were almost similar to those obtained in the previous version of experiment NV2: participants scored 28.8 % correct for audio-only slices and 46.4 % correct for visual-only slices. For the audiovisual slices, participants performed at chance level 35.4%. Apparently, the addition of sound to a video sequence deteriorates the identification of the winner. Figure 4.1 illustrates these results (reproduced from Tsay (2013)). The bar plot shows the percentage correct identification of the winner for each of the three presentation formats (audio-only, visual-only, and audiovisual). The horizontal dashed line represents the chance level of 33.3%.

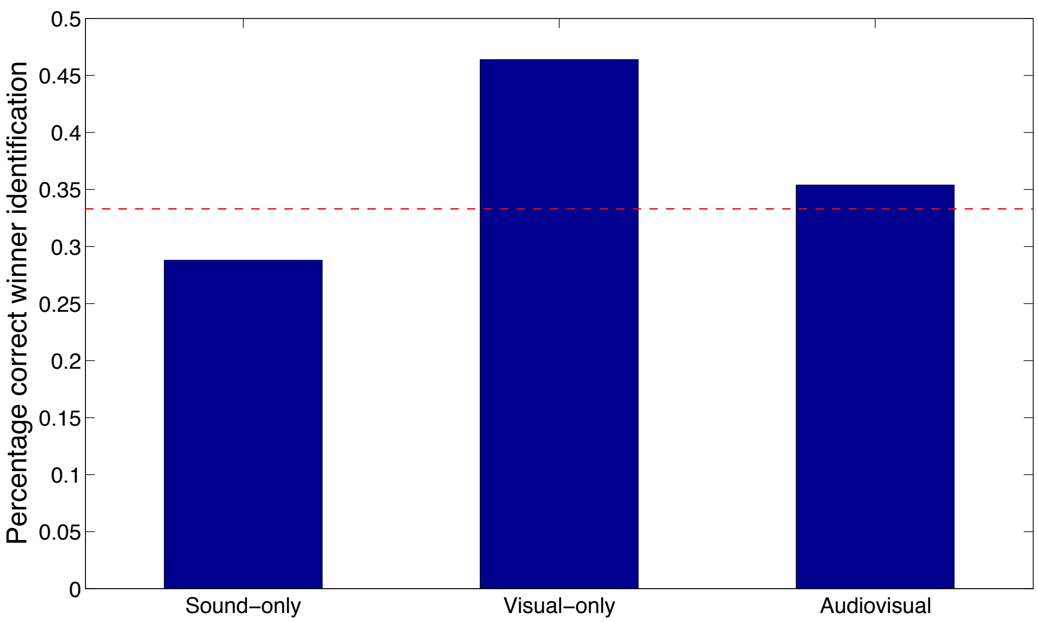

Figure 4.1: Bar plot showing percentage correct identification of winning musicians by novices (Experiment NV2). The three bars represent the identification performances obtained for three presentation formats: Audio-only, Visual-only, and Audiovisual. The horisontal dotted line represents the performance obtained by random guessing (chance level = 33.3%). The result is taken from Tsay (2013; experiment 3).

4.1.2 An Expert's Assessment

To determine whether experts would show a task performance different from that of novices, Tsay (2013) conducted two experiments with differently-sized samples of professional musicians: N = 35 and N = 106. We will refer to these experiments as E1 and E2, respectively. The results for experiment E1 were: 20.5 % correct for audio-only thin slices, 46% correct for visual-only, and 32.9 % correct for audiovisual slices. The results for experiment E2 involving the larger group of professional participants (N = 106) were quite similar: 25.7 % correct for audio-only, 47 % correct for visual-only, and 29.5 % for audiovisual slices. Comparing the results obtained in the experiments involving novices (NV1 and NV2) to those of the experiments with experts (E1 and E2) we established that there is no clear difference between novices and musical experts in the assessment of musical performance.

4.1.3 Dominance of Visual-only Information

Tsay's (2013) experiments clearly show the dominance of visual information in the identification of the winning musician among the three finalists of international competitions. Although it is not entirely clear on what visual cues the participants rely in their identification of the winner, it is quite likely that facial expressions play a major role. Most of the videos employed by Tsay contained (near) frontal shots of the upper body of the musician (shoulders and head). In addition, the participants in Tsay's study seemed to rely on the perceived passion of musicians as an important cue to identify the winner. Instructing participants to identify the most passionate musician of each triplet, yielded the identification of the winner in 59.6 % of the cases (Tsay, 2013).

The dominance of visual information in the assessment of a primarily auditory performance, allows for visually based inferences of musical performances. Having outlined Tsay's experiments in detail, we now turn to describing the set-up of the computational analysis of the thin slices of the finalists.

4.2 EXPERIMENTAL SET-UP

Our experiments are directly inspired by Tsay (2013)'s experimental results. In this section we describe the dataset used for our experiment (4.2.1), the coding of the facial expressions (4.2.2), the training and testing procedure (4.2.3, the classifier(4.2.4), and the evaluation (4.2.5).

4.2.1 Dataset

In order to be able to perform a computational version of Tsay's experiments, we needed video sequences (thin slices) of the three finalists of 10 prestigious international classical music competitions. To enable the computational coding of facial expressions, the thin slices should consist of frontal views of the finalists' faces. For the compilation of the video dataset, Tsay kindly provided us with url's to the videos used in her experiments. All competitions but one (which was no longer available on-line) were still available and could be successfully downloaded. While exploring the videos, we noted that many videos did not contain unoccluded frontal views of the faces of the musicians, as is required for our automatic facial expression coding to work properly. In fact, for only one of these competitions, all three finalists were frontally fully visible: the 8th International Franz Liszt Piano Competition (No.7 in Table 4.1). We therefore decided to include the triplets of video sequences of this competition into our video dataset and to collect novel sets of triplets for the remaining nine international piano competitions. The video sequences for these nine competitions, were downloaded via YouTube. Table 4.1 lists the 10 competitions and their abbreviations for which the videos were collected.

Table 4.1: List of piano competitions employed in the study and their abbreviations.

#	Name of Competition *Abbreviation*	Year
1	Aarhus International Piano Competition *Aarhus2015*	2015
2	International Chopin Piano Competition *Chopin 2010*	2010
3	International Chopin Piano Competition *Chopin2015*	2015
4	Van Cliburn International Piano Competition *vanCliburn1993*	1993
5	Cliburn International Junior Piano Competition *CliburnJun2015*	2015
6	Dublin International Piano Competition *Dublin2012*	2012
7	8th International Franz Liszt Piano Competition *8Liszt2008*	2008
8	Geneva International Music Competition *Geneva2014*	2014
9	Rubinstein International Piano Competition *Rubinstein2014*	2014
10	Wallace National Piano Competition *Wallace2015*	2015

Figure 4.2 gives an impression of the finalists and their facial expressions included in the dataset. The top two rows show the pictures of the winners. The middle two rows show the pianists that reached the second place. The bottom two rows are the pianists that ended on the third place.

All video editing was performed with QuickTime Player 7 on a MacBook Pro 13. From the videos, we selected fragments of varying lengths, but never less than 6 seconds (Tsay used 6-second slices in her main experiment, but reported that shorter

Figure 4.2: Illustrations of the finalists of 10 international piano competitions The top two rows show the winners, the middle two rows the pianists that reached the second place, and the bottom two rows the pianists that reached the third place.

slices of $1-3$ seconds and much longer slices of up to 60 seconds, did not change the pattern of results). For each triplet of pianists, we tried to select similar parts of the musical performance (often the finalists play the same piece). However, the main difficulty was to select a fragment of at least 6 seconds that showed the frontal face of the musician. In cases where it was not possible to select a contiguous sequence of at least 6 seconds, we collected two or three sub-fragments that together covered at least a 6-second period. The lengths of the resulting video fragments ranged from 6.9 to 63.6 seconds. At a frame rate of 30 frames per second the video fragments correspond with 206 to 1908 frames. In Table 4.2, for each international competition (using the abbreviations introduced in Table 4.1) the number of frames of each video fragment is specified for each the three finalists (ranks 1 to 3).

Table 4.2: The number of frames captured from video fragments of the three finalists (columns) of the ten competitions (rows).

		Rank		
#	Competition	1	2	3
1	Aarhus2015	299	326	386
2	Chopin2010	659	1020	982
3	Chopin2015	310	741	521
4	CliburnJun2015	546	918	206
5	vanCliburn1993	1444	543	452
6	Dublin2012	629	591	606
7	8Liszt2008	809	1581	718
8	Geneva2014	786	945	754
9	Rubinstein2014	654	317	387
10	Wallace2015	590	1496	1908

From these video fragments we extracted 100 randomised datasets for training and testing our classifier (see subsection 4.2.3), each of which was based on a different random sample of frames from each fragment. For each of the datasets, thin slices were selected to cover 6 seconds which corresponds to 180 frames. These 180 frames were randomly selected from the frames available in the video fragment (206 to 1908). As a result, we obtained $10 \times 3 \times 180$ (number of competitions $\times$ number of finalists $\times$ number of frames) instances. These instances constitute one instantiation of the dataset for training and testing the classifier.

The 100 datasets allowed us to perform multiple replications of our experiment. In each replication, another random sample of 180 frames from the video fragments is used.

It is important to remark that these replications should not be interpreted as independent experiments. The reason is that the randomised datasets are not independent due to the overlap in terms of the frames included. The overlapping frames in the randomised datasets for any given competition-rank combination will be larger if the number of frames as listed in Table 4.2 is smaller.

4.2.2 Facial Expression Coding

We performed automatic coding of the video fragments by means of the Computer Expression Recognition Toolbox (CERT; Version 5.1, build 1208::867:869M) developed by Littlewort, Whitehill, Wu, Fasel et al. (2011). Each frame of the thin-slice video fragments was coded in terms of action units (AUs) according to FACS4.4 (Ekman & Friesen, 1978a). For each frame, CERT outputs the estimates of the action unit intensities. We selected the 20 actions units listed in Table 4.3 as measures of facial expression. Hence, each musician is represented by 180 instances (frames), each of which is a 20-dimensional feature vector of real values, i.e., action unit estimates.

Table 4.3: The twenty facial action units used as measures of facial expression.

Action Units (AUs)
AU 1 (Inner Brow Raise)
AU 2 (Outer Brow Raise)
AU 4 (Brow Lower)
AU 5 (Eye Widen)
AU 6 (Cheek Raise)
AU 7 (Lids Tight)
AU 9 (Nose Wrinkle)
AU 10 (Lip Raise)
AU 12 (Lip Corner Pull)
AU 14 (Dimpler)
AU 15 (Lip Corner Depressor)
AU 17 (Chin Raise)
AU 18 (Lip Pucker)
AU 20 (Lip Stretch)
AU 23 (Lip Tightener)
AU 24 (Lip Presser)
AU 25 (Lips Part)
AU 26 (Jaw Drop)
AU 28 (Lips Suck)
AU 45 (Blink/Eye Closure)

4.2.3 Training and Testing Procedure

The automatic classification proceeds as follows. For each randomised dataset, we train a classifier on classifying $9 \times 3 \times 180$ instances of all but one competition (9 competitions, 3 finalists, and 180 frames per finalist). The classifying entails assigning each instance to either class "1", "2", or "3", representing the ranks in the finals. After being trained on the 9 competitions, the classifier is tested on the 10-th competition. This training and testing procedure is repeated 10 times, whereby each time a different competition is used for testing (i.e., 10-fold cross validation). After the 10 training-testing repetitions, the test results are averaged. This procedure is generally known as 10-fold cross validation. Each fold in this procedure tests the classifications of the three finalists of one competition.

Given that we have 100 datasets (obtained by different random samples of 180 frames of the video fragments), we repeat the cross-validation procedure 100 times. This allows us to report averages and standard deviations that provide insight into the dependency on specific samples of frames.

4.2.4 Classifier

Given the limited size of the dataset, we used a linear classifier, regularised Fisher's linear discriminant (Friedman, Hastie & Tibshirani, 2001), in which all classes are assumed to have the same diagonal covariance matrix. The classifier finds a linear combination of features that yields the best separation of two or more classes. After training, the classifier will be tested on instances of 180 frames each. Each instance yields three proportions (that sum to one). They are the proportion of rank=1 predictions, rank=2 predictions, and rank=3 predictions. The final classification is correct if the maximum proportion is associated with the actual rank of the instance. We report our classification results in terms of the proportion of correctly identified winners (the measure used in Tsay's study) and use them as entries in confusion matrices.

4.2.5 Evaluation

The classification results will be evaluated in three ways. First, we will apply the same evaluation criterion as used by Tsay: the proportion of correctly identified winners. In our experiment, this implies that we count the number of times that the algorithm correctly classified test instances labelled as "1" and divide that by the total number of instances labelled as "1". If the resulting proportion differs significantly from change level (0.33), we may conclude that the procedure extracted visual cues from the facial expressions that are predictive for the winner. Second, to obtain a complete insight into the classification behaviour we will report confusion tables for the entire experiment and for each fold (i.e., piano competition) of the cross-validation procedure, averaged over the 100 replications. Third, to establish the relative contribution of the 20 action units to the winner prediction performance, we determine the impact of removing one action unit from the feature vector on the prediction performance. Also for this experiment, the cross-validation results are averaged over the replications. Larger impacts indicate a larger contribution of the left-out action unit on the prediction.

4.3 RESULTS

Below, we provide results in two parts: the results of the main classification experiment (4.3.1) and the results of the analysis of the contributions of individual facial action units (4.3.2).

4.3.1 Results of Classification

The main results of the classification experiment is the proportion correctly identified winners. We obtained a proportion of 0.43 (0.01) correct, which is well above chance level. This indicates that the recognition of visual cues that are predictive for the winner can be performed by a computer and does not necessarily require a human.

Table 4.4 shows a normalised confusion matrix that summarises the overall performance on the classification task. The rows of the matrix are normalised to sum to 1. For the actual class equal to "1", each column shows the proportion of instances that were predicted to be the correct class "1", "2", and "3". As can be seen from the first row, the majority of instances are correctly classified. For each row, the largest proportion is printed in boldface. All numbers along the main diagonal are boldfaced indicating that, on average, the classifier performs better than chance on all three classes.

Table 4.4: Confusion matrix showing the results in video fragments of the actual rank (rows) and the predicted ranks (columns). Each entry shows the average cross-validation performance (and standard deviation), computed for the 100 replications. For each row (actual rank), the largest proportion is printed in boldface.

Confusion Matrix			
	predicted		
actual	1	2	3
1	**0.430** (0.010)	0.293 (0.012)	0.277 (0.008)
2	0.312 (0.001)	**0.410** (0.019)	0.278 (0.016)
3	0.240 (0.010)	0.317 (0.010)	**0.443** (0.017)

Table 4.5 shows the normalised confusion matrices for each competition separately. For 7 of the 10 competitions, (viz,. 3, 4, 5, 6, 7, 8, and 10), the winner is identified correctly. For Aarhus2015, Chopin2010, and Rubinstein2014, the algorithm fails to identify the winner.

4.3.2 Contribution of Individual Action Units

The contribution of individual action units to winner identification was assessed by performing the entire experiment while excluding one facial action unit from the feature vector. Figure 4.3 shows the results. Each box plot represents the distribution of scores obtained when the corresponding action unit (indicated on the x-axis) is removed. The biggest drop in performance is obtained by excluding Action Unit

Table 4.5: Confusion matrices for the 10 competitions. Each confusion matrix lists the actual ranks in the rows. (Ranks 1, 2, and 3 are represented by the top, middle and bottom row, respectively.) The predicted ranks are shown in the columns. (Ranks 1, 2, and 3 are represented by the left, centre, and right columns, respectively.) For each row (actual class), each entry represents the proportion of the 180 frames classified as the rank specified by the row. For the top row (the actual winner), the correct winner is predicted if the associated proportion in the first column has the largest value of that row. These correct predictions are printed in boldface.

Aarhus2015			Chopin2010		
Winner is incorrect			Winner is incorrect		
0.106	0.774	0.120	0.216	0.040	0.744
0.167	0.533	0.300	0.435	0.334	0.231
0.061	0.555	0.384	0.072	0.154	0.774
Chopin2015			VanCliburn1993		
Winner is correct			Winner is correct		
0.534	0.149	0.318	**0.355**	0.329	0.316
0.579	0.056	0.366	0.175	0.551	0.274
0.591	0.056	0.366	0.130	0.317	0.554
CliburnJun2015			Dublin2012		
Winner is correct			Winner is correct		
0.742	0.097	0.161	**0.508**	0.110	0.382
0.380	0.039	0.581	0.307	0.134	0.559
0.016	0.078	0.906	0.483	0.127	0.390
8Liszt2008			Geneva2014		
Winner is correct			Winner is correct		
0.575	0.315	0.110	**0.856**	0.039	0.105
0.267	0.381	0.352	0.303	0.673	0.024
0.007	0.351	0.643	0.385	0.483	0.132
Rubinstein2014			Wallace2015		
Winner is incorrect			Winner is correct		
0.402	0.512	0.086	**0.676**	0.261	0.063
0.232	0.635	0.133	0.520	0.118	0.362
0.727	0.132	0.141	0.731	0.036	0.234

12 ("Lip Corner Pull"), which suggests that this action unit has the largest relative contribution to the prediction.

Table 4.6 presents the same results as a sorted list of the average performances and their standard deviations. Given that the performance obtained with all 20 action units is equal to 0.43, it is interesting to see that starting with AU20 (Lip Stretch) downwards, removal leads to an improved performance, i.e., higher than 0.43. This may be due to the fact that these action units are harmful to the prediction. Their removal is beneficial. In addition, or alternatively, their removal mitigates the adverse effects of dimensionality (i.e., the curse of dimensionality).

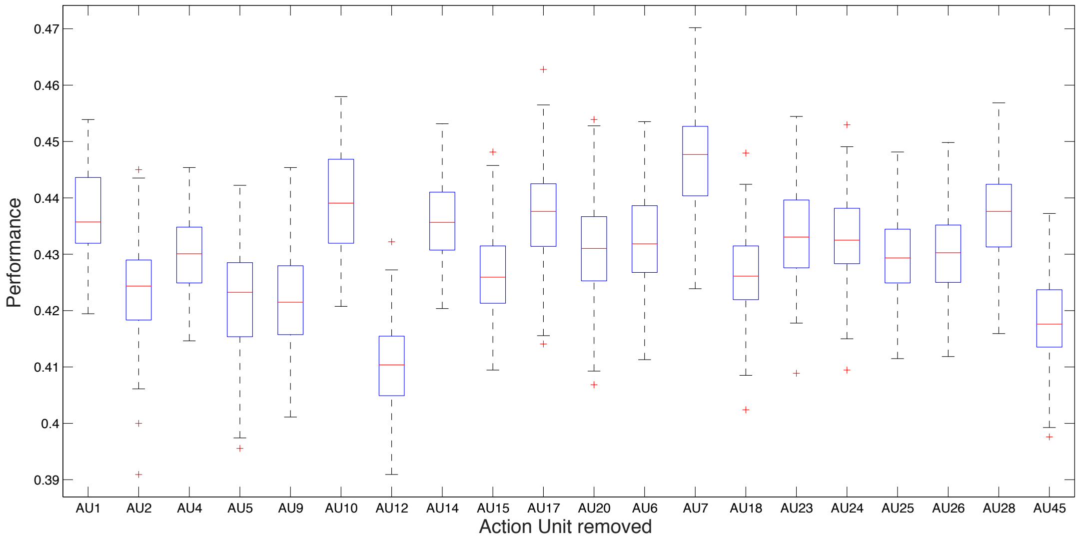

Figure 4.3: Box-whisker plots showing the distribution of performances obtained by removing one action unit and training the classifier on the remaining ones. The distribution is based on 100 replications with the randomised datasets.

Table 4.6: Performances obtained by removing one action unit and training the classifier on the remaining ones. The performances are listed in increasing order. The average performance and standard deviations are computed over 100 replications with the randomised datasets.

Action unit (AU) excluded	Performance of removing AUs	Standard deviation
(AU 12) Lip Corner Pull	0,411	0,0076
(AU 45) Blink/Eye Closure	0,418	0,0079
(AU 9) Nose Wrinkle	0,422	0,0087
(AU 5) Eye Widen	0,422	0,0092
(AU 2) Outer Brow Raise	0,424	0,0092
(AU 18) Lip Pucker	0,426	0,0076
(AU 15) Lip Corner Depressor	0,427	0,0077
(AU 4) Brow Lower	0,430	0,0070
(AU 25) Lips Part	0,430	0,0076
(AU 26) Jaw Drop	0,430	0,0078
(AU 20) Lip Stretch	0,431	0,0093
(AU 6) Cheek Raise	0,432	0,0087
(AU 24) Lip Presser	0,433	0,0081
(AU 23) Lip Tightener	0,433	0,0088
(AU 14) Dimpler	0,436	0,0075
(AU 28) Lips Suck	0,437	0,0078
(AU 1) Inner Brow Raise	0,437	0,0082
(AU 17) Chin Raise	0,437	0,0094
(AU 10) Lip Raise	0,439	0,0092
(AU 7) Lids Tight	0,447	0,0086

4.4 DISCUSSION

Our findings suggest that computers can identify winners at a level that is near that of human participants. We achieved a correct proportion of 0.43 (which may be further optimised with feature selection) as compared to the results of Tsay's experiments with novice and expert participants, i.e., 0.46 and 0.47, respectively.

It is important to note that the tasks faced by our computer and by Tsay's (2013) participants are rather different. Our computer had to be trained on all-but-one competitions to learn to recognise the facial characteristics associated with the first, second, and third place in the competition. The human participants relied on their previous (cultural) experience with competitions and performers to deliberatively identify the winner. We do not think that these differences invalidate our results. The differences arose mainly from data limitations. If we would have access to a much larger set of suitable videos, a closer approximation of the participant's task would have been feasible. It is likely that with a much larger set of videos (hundreds of competitions), the performance would be higher than the currently reported one. All in all, our results show that there is visual information that is captured in the action unit intensities that generalises from one competition to another.

The question remains what visual cues are used to predict the winner. In both Tsay's experiment and ours, there may be hidden cues, which may be considered to be task-irrelevant, but from a statistical perspective they are not. For instance, let us consider the task-irrelevant cue of gender. The gender of a pianist may be very well captured implicitly by the pattern of action unit estimates. If a male is more likely to be the winner of a competition than a female, gender becomes a useful cue for identifying the winner. Table 4.7 lists the gender composition in the datasets employed by Tsay and by us. In our dataset of 30 pianists, there are 9 female pianists against 21 male pianists. Given this gender base rate, the probability of a male winning is more than twice of that of a female winning. Tsay's dataset has a similar gender distribution: of the 27 pianists (excluding the three of the missing competition), 8 are female. So, in both cases the majority of potential winners are male. Therefore, exploiting gender-specific cues allows for above chance predictions of the winner. If our algorithm relied on gender-specific cues, it would always predict a male participant to be the winner and therefore fail on competitions where a female wins. Referring to Table 4.6 there are two competitions in which a female (F) is the winner: Geneva 2014 (FFM) and Chopin 2010 (FMM). As can be seen in Table 4.5, our algorithm identifies the correct winner for Geneva 2014, but not for Chopin 2010. Taken together with the other competition-specific performances, our results do not support the idea that gender-specific cues explain the winner identification.

Some insight into the nature of the cues responsible for the identification is provided by Figure 4.3. Of all action units, AU12 has the largest impact on performance. AU12 signals a subtle smile of the pianist during his or her musical performance. As revealed by Williamon and Davidson (2002) smiling is an important social signal in musical coordination and appreciation. Tsay's finding that perceived passion seems to contribute to the identification of winners, may be reflected in the top four action units with the largest contribution to the prediction performance, i.e., AU 12 (Lip Corner Pull), AU 45 (Blink/Eye Closure), AU 9 (Nose Wrinkle), and AU 5 (Eye Widen).

In what follows, we briefly discuss to what extent these action units may be related to the facial expression of passion. To the best of our knowledge, the relation of facial expressions and passion has not been studied so far. It is generally recognised that passion is a multifaceted notion. For instance, in their study of passion and musical excellence, Bonneville-Roussy, Lavigne and Vallerand (2011) distinguished between "harmonious passion" and "obsessive passion". In the context of musical performance, we assume that passionate musicians visibly experience the emotions conveyed by their musical performance. This implies that a passionate pianist tends to exhibit emotional facial expressions. The six basic facial emotional expressions (happy, sad, fear, anger, surprise, disgust) have been defined by combinations of

Table 4.7: Datasets used in our and Tsay's experiments The gender of the three finalists is indicated below each competition (F=Female, M=Male).

Our dataset	Tsay's dataset
Aarhus2015	San Marino 2008
1. M 2. M 3. F	1. M 2. F 3. M
Chopin2010	Hannover Violin 2009
1. F 2. M 3. M	1. M 2. F 3. F
Chopin2015	Queen Elizabeth Violin 2009
1. M 2. M 3. F	1. M 2. M 3. M
VanCliburn1993	Cliburn 1997
1. M 2. M 3. M	1. M 2. M 3. M
Cliburn Junior2015	Cliburn 2009
1. M 2. M 3. F	1. M 2. M 3. M
Dublin2012	Tchaikovsky*
1. M 2. M 3. M	Unknown
8Liszt2008	8Franz Liszt 2008
1. M 2. F 3. F	1. M 2. F 3. F
Geneva2014	7Franz Liszt 2005
1. F 2. F 3. M	1. F 2. M 3. M
Rubinstein2014	6Franz Liszt 2002
1. M 2. M 3. M	1. M 2. M 3. F
Walace2015	Cleveland 2009
1. M 2. M 3. F	1. F 2. M 3. M

* This video had been revoked from YouTube.

action units (Ekman & Friesen, 1978a). A more recent computational study even defined twenty-one so-called compound emotional expressions that include combinations of emotional expressions, such as "happily surprised" and "fearfully angry"

(Du, Tao & Martinez, 2014). Relating our top four action units to the extended set of emotional expressions, may offer a proxy for passionate musical performances.

The front-ranked action unit in our study, AU12, is associated with happy expressions. The runner-up, AU45, signals eye closure which may be associated with concentrated play. Indeed, visual inspection of the thin slices revealed that many winning finalists closed their eyes during substantial parts of their performance. The third action unit, AU9 (nose wrinkle), is associated with the emotion of disgust. Examination of the thin slices did not show the expression of disgust at the finalists, but did show the nose wrinkle as part of what could be called a “passionate" expression. Finally, AU5, is part of three of the twenty-one emotional expressions discovered by Du et al. (2014): “fearfully surprised”, “disgustedly surprised,” and “awe”. Especially, the latter may be related to passion. Obviously, these qualitative observations are insufficient to establish a firm relation of our findings with the assessment of passion by the participants in Tsay (2013)’s study. Further research is needed to define passion in terms of action units.

4.5 ANSWER TO RQ3

Our computational study of the facial expressions of pianists in the finals of international competitions provided relevant insights into the objective presence of visual cues for predicting the winner. Our results allow us to answer the research question, which we restate below.

RQ3: To what extent do facial expressions allow for the identification of winning musicians?

Our findings show that facial expressions allow for the identification of the winning musician to an extent that almost matches the performance of human participants. This leads us to conclude that we were able to achieve near-human prediction performance on the task of determining the winner of music competitions on the basis of facial expression information only.

Future research will broaden the investigation to include different types of competitions (e.g., song contests) in order to determine to what extent winners across different types of competitions share similar visual facial cues.

5 THE FACIAL EXPRESSIONS OF LEADERSHIP

The relation between facial appearance and leadership have been studied before. We mention six prominent examples. First, Humphrey (2002)published a remarkable article titled *The many faces of emotional leaderships*. The main observation was that to an observer, the effects of the facial expressions accompanying a message had a stronger effect than the content of the message. Second, Todorov, Mandisodza, Goren and Hall (2005) studied how faces of congressional candidates influence inferences about their competences. They found that faces induce rapid trait inferences that can affect voting choices. Third, Zebrowitz and Montepare (2005) found that facial maturity affects the judgements of leadership. Fourth, Rule and Ambady (2008) reported that the success of companies can be predicted from the facial appearances of their chief executive officers. Fifth, Rule and Ambady (2011) found that first impressions of Managing Partners (MPs) of law firms are significantly correlated to the financial success of the firms. Sixth, (Aviezer, Trope & Todorov, 2012) changed the ideas on the power of facial expressions by their publication *Body cues, not facial expressions, discriminate between intense positive and negative emotions*. These six examples showed, each on their own way that facial appearance contributes to leadership and success. However, these studies did not focus on the relation between the specific element of facial expressions and also not on their relation with leadership traits.

In this chapter, we will investigate the relation between facial expressions and leadership traits. We start our research by investigating the work by two of Humphrey's (2002) colleagues, viz. Newcombe and Ashkanasy (2002). They showed the importance of the congruence of facial and verbal expressions for leaders. They found that leaders whose facial expressions were congruent with their verbal expressions were assessed more positively, than those whose expressions were incongruent with their verbal expressions. For instance, in terms of leadership rating, positive verbal feedback accompanied with negative facial expressions was rated lower than negative verbal feedback with negative facial expressions. A similar finding was somewhat earlier obtained by Bucy and Newhagen (1999). They found that observers who assessed leadership in the context of public speeches and other public appearances, considered negative and low intensity emotional expressions more appropriate than positive displays.

In that time (1999), the following was already mentioned. Negative and low intensity expressions are more congruent with the expected behaviour of a leader in public appearances. However, they should not be taken to imply that leaders are characterised by negative expressions. Otta, Lira, Delevati, Cesar and Pires (1994) studied how smiling affected leadership ratings. The general finding was that leaders who smiled were assigned higher ratings, than those who did not. In line with these results, Masters and Sullivan (1989) showed that the emotional responses of viewers were positively influenced by positive and reassuring facial expressions of political leaders. These examples illustrate two important points about the relation between facial expressions and the assessment of leadership traits. First, there *exists* a relation between facial expressions and the assessment of leadership. Second, the relation between facial expressions and the assessment of leadership is *context-dependent*. Presumably, there exist leadership-specific display rules for facial expressions (see chapter 1).

The focus of this chapter is on facial expressions and the assessment of leadership. More specifically, the following research question is addressed.

RQ4: *What is the relation of dynamic facial expressions to leadership assessment?*

The fascinating run-up to RQ4 has been given in the beginning of this chapter. On research overview ended in 2012. That was the few when a second seminal publication appeared by two authors who later showed to be influential authors in this field: (Trichas & Schyns, 2012). Their study aimed to determine how facial expressions influence leadership perception in terms of Implicit Leadership Theory (ILT) (cf. Foti & Lord, 1987; Offermann, Kennedy & Wirtz, 1994). It was a prominent theoretical discourse on the perception and assessment of leadership that gave rise more recent publications, (Trichas, 2015; Trichas, Schyns, Lord & Hall, 2017). Therefore, we set out to perform our exploratory survey and computational investigation on the relation between dynamic facial expressions and leadership.

The outline of the chapter is as follows. Section 5.1 briefly introduces Implicit Leadership Theory and reviews the study by Trichas and Schyns (2012). Then, in section 5.2, we turn to our study by describing the research method employed in our behavioural and computational analyses. The results are presented in section 5.3. Finally, section 5.4 discusses the results, answers RQ4, and then concludes on the relation between dynamic facial expression and the assessment of leadership.

5.1 IMPLICIT LEADERSHIP THEORIES AND FACIAL EXPRESSIONS

We start briefly introducing Implicit Leadership Theory (subsection 5.1.1). Then a concise overview of the study by Trichas and Schyns (2012) is given in subsection 5.1.2. Subsequently, the experiment that is most relevant to our research question is discussed in detail in subsection 5.1.3. Finally, in subsection 5.1.4, we evaluate the study and motivate our approach.

5.1.1 Implicit Leadership Theory

Implicit Leadership Theory (ILT) was initially proposed by Robert Lord and colleagues (Foti & Lord, 1987). The theory is based on the assumption that members of a group have expectations, beliefs, and assumptions about their leaders and about leadership. These expectations, beliefs, and assumptions are called "implicit leadership theories" (ILTs), because, similar to formal theories, they include generalities about leadership and hypotheses about the qualities that characterise most leaders (cf. Lord, Foti & De Vader, 1984; Lord & Maher, 2002). Kenney, Blascovich and Shaver (1994) defined ILTs as people's expectations of leaders' qualities and behaviours, based on previous experiences with leaders. Hall and Lord (1995) argue that people use their ILT as a reference point for the evaluation of the leadership traits of a potential leader. The result of the evaluation determines the degree to which an individual is categorised as a leader (cf. Hall & Lord, 1995). The expectations, beliefs, and assumptions about general behavioural characteristics and traits in ILTs, are widely believed to include those pertaining to facial expressions and prompted Trichas and Schyns (2012) to perform an experimental investigation of facial expressions and leadership.

5.1.2 Overview of the Trichas and Schyns (2012) Study

Trichas and Schyns (2012) aimed at assessing the influence of facial expressions on leadership assessment. They determined which facial expressions influence perceptions of leadership and how these facial expressions affect perceptions of leadership. Their study consisted of two phases and five behavioural experiments in total.

Phase 1

Phase 1 was in fact a pilot study on how leadership perceptions are formed from facial expressions. It contained two experiments: experiment 1 (98 participants) and experiment 2 (60 participants). Since the experiments were similar we describe the once below. Participants' prototypes of leadership were assessed by means of a survey of 49 items that measure trait characteristics which define the ILT. Additionally, the participants were asked to evaluate pictures of different facial expressions. Factor analysis was applied to the survey results. Factor analysis is a statistical method that maps observed correlated variables onto a potentially lower number of unobserved variables called factors. The number of factors obtained depends on the number of observed variables and their correlations. In the Trichas and Schyns (2012) study, the observed variables are the 49 item responses, and the unobserved variables are the leadership characteristics. Factor analysis mapped the 49 trait characteristics with 11-point scale onto 10 factors. Each of these factors form a linear combination of item responses and are assigned meaningful names that summarise or characterise the underlying items. (Sometimes the factor is assigned the same name as that of one of the underlying items.)
The 10 factors were labelled as follows: *Sensitivity*, *Credibility*, *Intelligence*, *Dedication*, *Dynamism*, *Likeability*, *Social skill*, *Tyranny*, *Dominance*, and *Masculinity*. The results suggested that the participants used all available information, including facial appearance, expression, context of communication, appropriateness, and authenticity of expression to form complex prototypes of leadership.
The relatively small number of participants (98 Cypriot full time undergraduate business students in experiment 1 and 60 Cypriot postgraduate part time M.B.A students in experiment 2) of the first phase of the study prompted a second phase of the study,

involving a considerably larger number of participants (807 Cypriot bank employees).

Phase 2

Phase 2 consists of three experiments (experiments 3-5). The number of participants per experiment are 204 participants in experiment 3, 231 participants in experiment 4, and 372 participants in experiment 5. The aim of the three experiments was to certify or to improve upon the two pilot studies (of phase 1). (Trichas & Schyns, 2012) used the following means increasing the number of participants and refining the methodologies. As in phase 1, participants' ILTs were assessed. In phase 1 the 49-item ILT survey was mapped on 10 factors. In phase 2, the survey was reduced to 38 items to accommodate feedback from participants. The results were mapped to 8 factors. The 38 items were measured by 9-point scale. The reason of reducing factors in phase 2 is because the 10 factors that were representing the 49 ILT items in phase 1 were considered a risk for the questionnaire's validity (too demanding for the participants). Therefore, in the questionnaire of the phase 2 study contains the 38-item survey that mapped to the 8 factors were named *Intelligence*, *Sensitivity*, *Dynamism*, *Tyranny*, *Potency*, *Masculinity*, *Likeability*, and *Dedication*. Appendix J list the ILT factors and the ILT items used in Phase 1 and Phase 2. Moreover table 5.1 lists the 38 items of the reduced ILT survey.

Here we ask the reader to note the differences with the list of 10 leaderships factors above. We see that seven factors are the same (*Intelligence*, *Sensitivity*, *Dynamism*, *Tyranny*, *Masculinity*, *Likeability*, and *Dedication*). The remaining factor in the 8-factors list is *Potency*. This *Potency* factor replaces the factors of the 10-factors list, viz. *Credibility*, *Social Skill*, and *Dominance*. From the publication of Trichas and Schyns (2012) we derive that the definitions of the newer concepts mentioned above are the same in both lists, the 10-factor list and the-8 factor list. Trichas and Schyns (2012) performed three distinct experiments in phase 2. First, experiment 3 is to investigate the relation with ILT and the manipulation of static facial expressions. Second, experiment 4 is to discover dynamic facial expressions and leadership perception. Third, to compare leadership perception to static facial expressions and dynamic facial expressions. From the three experiments we single out experiment 4 and address the relationship between dynamic facial expressions and leadership assessment as handled by Trichas and Schyns (2012). This experiment will be discussed in detail in sub section 5.1.3

5.1.3 Dynamic Facial Expression and Leadership

In experiment 4, Trichas and Schyns (2012) set out to determine if positive facial expressions (i.e., expressions with indicators of happiness, e.g., smiling) are positively related to leadership assessment and negative facial expressions (expressions with indicators of anger, or sadness, e.g., eyebrow lowering, and pulling eyebrows together) are negatively related to leadership assessment. We reiterate that in phase 2 Trichas and Schyns obtained 8 leaderships factors, whereas in phase 1 they ob-

Table 5.1: 38 ILT's traits

No	Trait	No	Trait	No	Trait
1	Understanding	14	Motivated	27	Manipulative
2	Sincere	15	Dedicated	28	Conceited
3	Compassionate	16	Hard-working	29	Selfish
4	Helpful	17	Bold	30	Loud
5	Sensitive	18	Dynamic	31	Credible
6	Warm	19	Strong	32	Stressed
7	Forgiving	20	Energetic	33	Uncertain
8	Intelligent	21	Confident	34	Smiling
9	Clever	22	Determined	35	Likeable
10	Knowledgeable	23	Charismatic	36	Competent
11	Educated	24	Domineering	37	Attractive
12	Wise	25	Pushy	38	Feminine
13	Intellectual	26	Dominant		

tained 10 leadership factors. In the experiment, Trichas and Schyns (2012) provided 231 bank employees (55.1% male) with (1) a short survey, (2) an acted scenario presented by means of a 14-second video, and (3) the (reduced) ILT survey. In the short survey, participants were asked to answer open-ended questions about leadership. The scenario consisted of two segments showing an actor that played the head of an HRM (Human Resource Management) group.

In the first segment (which was the same for all participants) the actor (playing the HRM manager) showed a neutral expression, followed by a smile as he greeted the person he was talking with (a HRM team member). Subsequently, the manager frowned as he was listening to the problem as explained by his HRM team member. In the second segment, the actor (the HRM manager) gave a solution to the problem.

The second segment had three different variants for three different groups of participants. The first variant used a facial display with indicators of happiness (presented to $N = 63$ participants), the second variant used a facial display with indicators of nervousness ($N = 58$), and the third variant used a facial display with indicators of anger ($N = 66$). (The remaining 44 participants were not given a video presentation and only filled in the short survey.) After watching their video, all 187 participants completed the ILT survey. Post-hoc manual FACS coding confirmed that the actor generated the three types of expressions (*happiness*, *nervousness*, and *anger*) appropriately.

The results revealed that participants assigned higher leadership scores for the acted happy expression, than for the acted nervous and angry expressions. The same was true for seven out of the eight leadership factors: *Intelligence*, *Dynamism*, *Tyranny*, *Masculinity*, *Likeability*, *Sensitivity* and *Dedication*. The only factor that did not show any difference in scores for the three expressions was *Potency*. Table 5.2 list the factor scores (defined on a nine-point scale ranging from 1 (*not at all characteristic*) to 9 (*extremely characteristic*) for the eight leadership factors (ranked from largest to smallest score for the smiling expression). Comparison of the factor scores for the three facial expressions reveals that the scores for *Intelligence*, *Likeability*, *Dedication*, and *Sensitivity* are largest for smiling (happiness), intermediate for nervous, and smallest for angry expressions. The reverse is true for the scores for *Tyranny*. For *Dynamism*, *Masculinity*, and *Potency*, neither pattern applies.

Table 5.2: A comparison of the scores on the eight leadership factors (second column) for the three facial expressions (third to fifth column). All scores are defined on a nine-point scale, ranging from 1 (*not at all characteristic*) to 9 (*extremely characteristic*). The results are taken from Trichas and Schyns (2012)

No.	Leadership Factor	Score Smiling	Score Nervous	Score Angry
1	Intelligence	6.73	5.31	5.09
2	Likeability	6.44	4.24	3.24
3	Dedication	6.21	5.10	4.52
4	Sensitivity	5.98	4.63	3.58
5	Dynamism	5.32	3.58	4.20
6	Masculinity	4.62	5.31	2.84
7	Potency	4.16	3.75	3.81
8	Tyranny	3.24	3.83	4.48

5.1.4 Evaluation and Motivation

Having described the most relevant experiment of the Trichas and Schyns (2012) study, we now turn to (i) an evaluation of the merits and shortcomings of the experiment, and (ii) a motivation of our study in relation to the Trichas and Schyns (2012) study.

Merits and Shortcomings

The merits of the Trichas and Schyns (2012) study are threefold. First, it identifies the constituent factors underlying leadership. Second, it is the first study that manipulates dynamic facial expressions in a semi-realistic setting to determine the effect on the ILTs in terms of leadership factors. Third, it shows that dynamic facial expressions affect the leadership assessment as reflected in the leadership factors.

Despite these merits, the study falls short in four respects. First, the facial expressions were not spontaneous but acted. Although Trichas and Schyns (2012) relied on a professional actor that employed an acting technique that tries to create expressions that are as realistic as possible, they are likely to differ from natural expressions in the wild. As a consequence, the ecological validity of their findings may be limited. Second, only one actor was used whose appearance and idiosyncratic behaviours may have introduced a bias in leadership assessments. Third, the repertoire of expressions was restricted to four types (neutral and the three different expressions (happiness, nervousness, and anger)), which ignores potential effects of individual action units or of other emotional expressions. Fourth, technological advances have made manual FACS coding obsolete and may result in more precise and fine-grained coding of facial expressions.

Our motivation

In what follows, we describe our motivation for answering the research question (*What is the relation of dynamic facial expressions to leadership assessment?*) by addressing the four shortcomings of the Trichas and Schyns (2012) study. In general, we are motivated by using natural videos and intelligent computer applications. Our remedies are as follows. (1) We will employ (more or less) natural videos of contestants in a leadership competition. (2) Rather than relying on a single actor, we use multiple contestants to study the relation between facial expressions and leadership assessment. (3) Instead of analysing four types of facial expressions, we study the entire gamut of facial action units. (4) We rely on the automatic coding of facial expressions to obtain more precise and fine-grained estimates of facial expressions.

5.2 RESEARCH METHOD OF RQ4

Our investigation of the relation of facial expressions to leadership assessments consist of three parts. The first part consists of a survey of a participant's assessments of video sequences of potential leaders (5.2.1, 5.2.2, 5.2.3, and 5.2.4) [6]. The second part consists of the automatic coding of the facial expressions of the video sequences (5.2.5, 5.2.6) and the announcement on how we found the relations between leadership factors and action units (5.2.7). The third part is discussed in 5.3.

5.2.1 Survey Study

We used the same reduced ILT survey as in the Trichas and Schyns (2012) study. The survey was performed with Qualtrics[7] for the collection and initial reporting of response data. Below, we describe the participants, the stimuli, the experimental procedure, the analysis of the survey responses, the analysis of the video fragments, and the analysis of their combination.

5.2.2 Participants

In total 45 participants (13 females and 32 males) were invited to participate in the survey while attending a lecture. All participants were first-year students in the Communication and Information Sciences program of Tilburg University. In advance, we remark that this group differs from the group 231 of employee in (Trichas and Schyns

6 We are indebted to Dhiratara Widya who as Master student in Communication and Information Sciences, Tilburg University, helped us to collect the data

7 https://www.qualtrics.com/

(2012)) in age, maturity, and cultural background. It is impossible to eliminate the effect of these differences, but it does not withhold us from a control investigation with the same approach. The participants accepted the invitation (average age = 18,75 years old, SD = 1,65). They were assigned to rate video fragments of 5 seconds in length (see Stimuli below).

5.2.3 Stimuli

The stimuli for the survey were obtained from *www.youtube.com*. Profile videos were obtained of 33 female *JKT48 competition* contestants. JKT48 (JaKarTa 48) is an Indonesian song contest, which we selected for its emphasis on leadership. Part of the contest consists of a competition in which a leader has to be appointed for each team. Each contestant creates a profile video of herself in which she promotes her leadership abilities. The profile videos consist of the contestant providing some personal information and motivating her participation in the JKT48 contest. Throughout the profile videos, the contestants were facing the camera. All videos had a resolution of 1920×1080 pixels with a frame rate of 25 frames per second. We extracted representative thin slices (video fragments) of a duration of 5 seconds from the profile videos. Given a frame rate of 25 frames per second, this corresponds to 125 frames per fragment. The videos were edited using iMovie 13. Figure 5.1 gives an impression of frames of the selected fragments. Appendix G provides a list of the video URLs.

Figure 5.1: Figure with frontal views of JKT48 contestants. From left to right: Ve, Baby, Desy, Shani, and Elaine.

5.2.4 Experimental Procedure

To measure the leadership assessments of the JKT48 contestants, each participant completed the reduced 38-item ILT survey used by Trichas and Schyns (2012) for each profile video. To keep the task assigned to each participant manageable, we partitioned the 33 videos into three groups of 11 videos and assigned each of the 45 participants to one of these groups. As a result, each group of 11 videos was assessed by 15 participants.

Using the Qualtrics environment, the survey was presented in the following three steps (Appendix I). In the first step, the purpose of the experiment was explained and demographic information was requested (gender, age, nationality and educational degree). In the second step, participants were instructed to imagine that they were watching a TV show without sound and saw a person that they considered to be a leader. They were instructed to list the personality traits that, in their opinion, were characteristics for a successful leader. To this end, they were instructed to use a slider to assign a value to each of the 38 ILTs traits. The slider ranges from 1 to 9, with 1 ="not all characteristic" and 9 = "extremely characteristic". The initial positions of all slides was on 5 (in the middle). In the third step, the participants were presented 11 video-survey pairs. For each pair, they watched the 5-second video fragment and completed the accompanying ILT survey. All video-ILT survey pairs were presented on single scrollable pages.

5.2.5 Automatic Coding of Video Fragments

The second part consists of the automatic coding of the facial expressions of the video fragments. All thin slices were coded by means of the Computer Expressions Recognition Tool (CERT) to obtain the set number of datasets based on FACS (Facial Action Coding System) (Ekman & Rosenberg, 1997). CERT estimates for each frame the presence of facial action units. Each video contained 125 frames. The action unit estimates were averaged over these frames to obtain an average action unit estimate for each video.

5.2.6 Analysis of ILT Surveys

To visualise the structure of the ILT survey responses, we performed a canonical correlation analysis. In addition, the results of the ILT surveys were submitted to a factor analysis (cf. Trichas & Schyns, 2012) to identify the underlying leadership factors. To perform both analyses, the survey results were imported into IBM SPSS Statistics (Version 22). For the factor analysis we used principal component analysis (PCA) with varimax rotation.

5.2.7 The Relation between Leadership Factors and Action Units

The final analysis consist of a correlation analysis of average action unit estimates with the extracted leadership factors. To this end, Matlab (version 2014B) was used to compute and visualise the correlation matrix.

5.3 RESULTS

This section presents the third part of our investigation on the relation of facial expressions to leadership assessment. We discuss the results of the analyses of the ILT surveys (5.3.1), the extracted action units (5.3.2), and the correlation analysis (5.3.3). Here we remark that we did not find any significant effects of demographics (gender, age, nationality, and educational degree).

5.3.1 Correlation Analysis of Survey Data

We collected 11 completed ILT surveys per participant. The total number of surveys equals $33 \times 11 = 363$ (number of participants $\times$ ILT surveys). Preliminary examination of the results revealed that in 4 of the completed surveys all 38 sliders were left in their initial position (5). We assumed that the participants did not fill in these surveys and hence discarded the results. This left us with 359 surveys for analysis. We employed the canonical correlation for visualisation of the clustering of the 38 ILT items. Figure 5.2 visualises the result. The matrix shows the pairwise correlations of the 38 items. The correlations are colour-coded. White entries represent high correlations (near 1), whereas black entries indicate low correlations (near -1). The rows and columns of the matrix are sorted to encourage the spatial clustering of highly correlated items. In the middle of the matrix, a white square is visible. This square represents the highly correlated cluster of 6 items, i.e., the traits *Wise*, *Intellectual*, *Clever*, *Educated*, *Intelligence*, and *Knowledgeable*. The high correlations amongst these 6 traits indicates that the associated items probe the same underlying factor or general trait, which may be called *Intelligence*. Although less prominent, some smaller square regions can be discerned along the main diagonal. For instance, the 4 items *Compassionate*, *Helpful*, *Understanding*, and *Sincere*, seem to be strongly correlated. Overall, the visualisation of the survey data suggests that there is quite some clustering of items. In turn, this observation may lead to the idea that factor analysis can reduce the 38 items to a much lower number of factors.

5.3.2 Factor Analysis of ILT Survey Data

We applied a factor analysis with PCA (varimax rotation) to the 38-item ILT surveys as obtained from the 33 thin slices. After applying PCA, all items were retained, because their communalities were all good (> 0.55) (cf. Comrey & Lee, 2013; Yong & Pearce, 2013; Tabachnick & Fidell, 2007). The communality of an item can be understood as the proportion of variation in that item explained by all factors resulting from the factor analysis. The highest communality was associated with the survey item "intellectual" with a communality $= 0.89$, while the survey item "loud" had the lowest communality (0.55). The best structure that emerged from PCA was a 6-factor solution. Table 5.4 lists the factor loadings for the 6-factor solution. These 6-factors of leadership explain more than 60 % of the total variance. Here we remark that our factor analysis has reduced the number of factors to 6 which we labelled with the following meaningful names: *Intelligence*, *Sensitivity*, *Tyranny*, *Dynamism*, *Likeability*, and *Uncertainty*. When comparing these names to the 10 and 8 factor names assigned by Trichas and Schyns in phases 1 and 2 of their study, we see that the first five of our factor names correspond to those of both phases of the Trichas and Schyns study. For phase 1, the remaining 5 factor names were: *Credibility*, *Dedication*, *Social skill*, *Dominance*, and *Masculinity*. For phase 2, the remaining 3 factor names were: *Potency*, *Masculinity*, and *Dedication* (For detail see Appendix J). The only factor name unique to our study is *Uncertainty*, but this factor does not have a satisfactory consistency (see below). Using the same names for five factors is motivated by the fact that in our factor analysis the ILT items are grouped similar to those of Trichas and Schyns

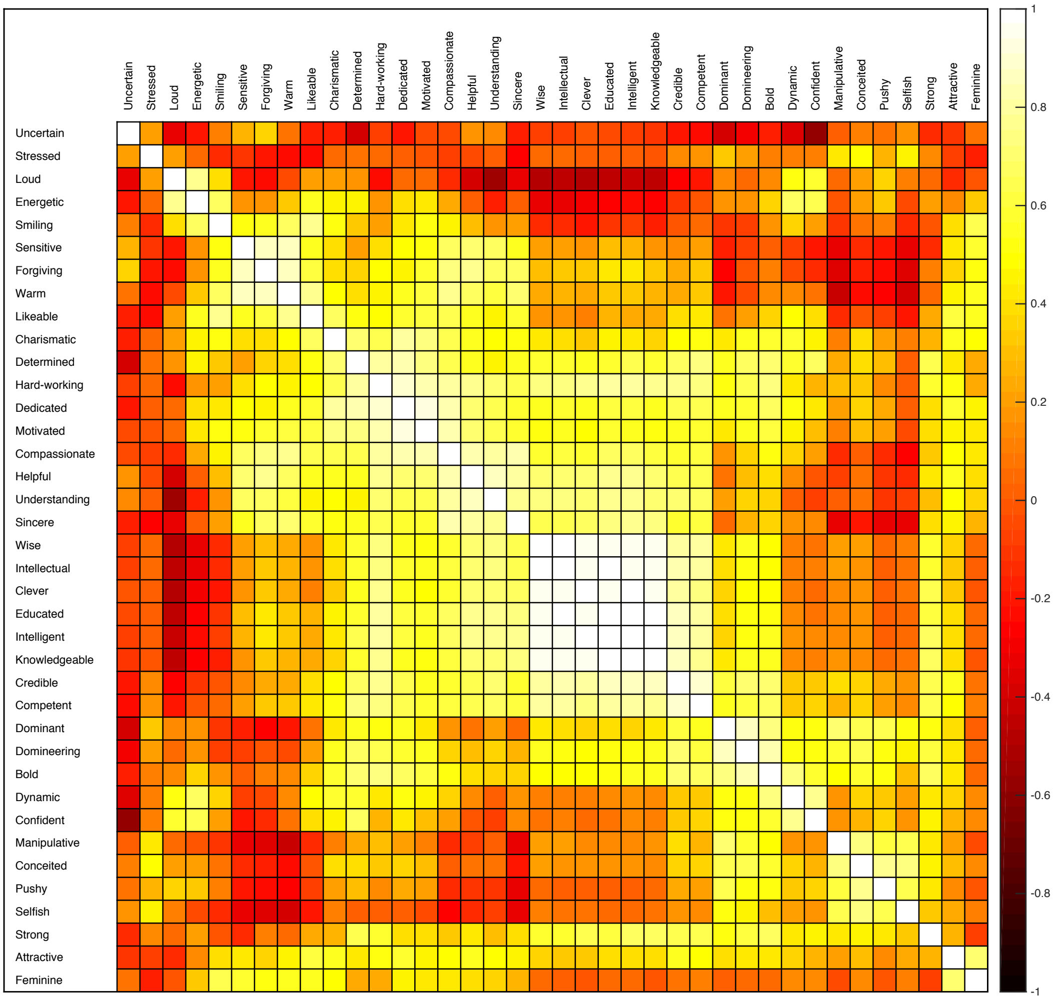

Figure 5.2: Correlation results of the 38 items of the ILT surveys. The correlation values are colour-coded and range from black (-1) to white (+1). The rows and columns of the matrix are sorted to encourage the spatial clustering of highly correlated items.

(2012) items. Table 5.3 indicates the comparison results of ILT factors of Trichas and Schyns (2012) in the phase (2) and our ILT factors. The five columns of the table list (from left to right) the factor number (No). the factor name assigned in Phase 2 of the Trychas and Schyns study (Phase 2), the items covered by each factor (Items), the factor names assigned in our experiment (Our findings), and the items covered by each of our factors (Items) table 5.3)

To provide support for the 6-factor solution two statistical tests were applied, viz. the Kaiser-Meyer-Olkin (KMO) statistic and the Cronbach α test. The KMO statistic is a test to evaluate the factorability of the items under consideration. The KMO statistics of the 6-factor model was equal to 0.94. Values above 0.90 are considered to be very good (cf. Yong & Pearce, 2013).

The Cronbach α test was conducted to check the internal consistencies (reliability) of the items within each factor. Table 5.5 lists the descriptive statistics: No of items,

Table 5.3: Comparison result of ILTs Factors between Trichas and Schyns (2012) Study in Phase 2 and Our Findings

No	Phase 2	Items	Our Findings	Items
1	Intelligence	Clever, Intelligence, Knowledgeable, Educated, Wise	Intelligence	Clever, Intelligence, Knowledgeable, Educated, Wise, Credible, Hard-working
2	Sensitivity	Compassionate, Sensitive, Helpful, Forgiving, Sincere, Understanding, Warm	Sensitivity	Compassionate, Sensitive, Helpful, Forgiving, Sincere, Understanding, Warm
3	Tyranny	Conceited, Selfish, Manipulative, Loud, Uncertain, Pushy, Domineering, Stressed, Dominant	Tyranny	Conceited, Selfish, Manipulative, Pushy, Uncertain,Domineering, Dominant
4	Dynamism	Confident, Determined, Dynamic, Energetic, Bold,	Dynamism	Confident, Determined, Dynamic, Bold, Strong, Loud, Dedicated, Motivated
5	Likeability	Likeable, Smiling	Likeability	Attractive, Likeable, Feminine, Smiling, Charismatic
6	Masculinity	Femininity/Masculinity, Female/Male, Attractive	Uncertainty	Stressed, Uncertain
7	Potency	Intellectual, Wise, Intense, Strong		-
8	Dedication	Motivated, Dedicated, Hard-working		-

Mean, Standard Deviation (SD), Skewness, and Kurtosis. The last column shows Cronbach's α coefficients. Assessing Cronbach's α, the reliabilities of five of the six factors were satisfactory (i.e., $\alpha \geqslant 0.75$): *Intelligence*, *Sensitivity*, *Tyranny*, *Dynamism*, and *Likeability*. For the factor of *Uncertainty* the value was not satisfactory ($\alpha = 0.61$). The low value of α may be due to the fact that the factor *Uncertainty* represents two items only (*Uncertainty* and *Stressed*), even the items have good communalities value (*Uncertain*= 0.78 and *Stressed*=0.79).

Although Table 5.5 shows a rather nice insight into the means of the leadership factors, figure 5.3 does a better job by illustrating the means as a radar plot. The distances of the corners of the hexagonal shape to the centre point (0), reflect the relative importance of the six factors in assessing leadership.

5.3.3 Results of the Correlation Analysis

The results of the canonical correlation analysis of 28 action units and the 6 leadership factors gave rise to a few correlations with $p < 0.05$. It is important to emphasise that these correlations are not "significant" as they would be in the context of a confirmatory analysis.

In our exploratory analysis, we selected the conventional p-value of 0.05 to signal potentially relevant relations between facial action units and leadership factors. Given the fact that we computed $28 \times 6 = 168$ correlations, we would expect more than eight spurious correlations. Therefore, we should interpret the current results with reservation.

Table 5.4: Results of the factor analysis applied to the ILT survey responses. The table lists the factor loadings for the 6 factors and the communalities (h^2) for each of the items.

No	Items	Factors						h^2
		1	2	3	4	5	6	
1	Intellectual	0.91						0.90
2	Educated	0.90						0.89
3	Knowledgeable	0.90						0.88
4	Clever	0.90						0.88
5	Intelligent	0.90						0.89
6	Wise	0.90						0.87
7	Credible	0.70						0.63
8	Competent	0.66						0.66
9	Hard-working	0.60						0.76
10	Forgiving		0.80					0.77
11	Compassionate		0.79					0.77
12	Warm		0.78					0.79
13	Sensitive		0.78					0.73
14	Sincere		0.72					0.70
15	Helpful		0.71					0.79
16	Understanding	0.51	0.67					0.72
17	Selfish			0.85				0.73
18	Manipulative			0.85				0.76
19	Conceited			0.84				0.74
20	Pushy			0.80				0.70
21	Dominant			0.74				0.74
22	Domineering			0.58				0.67
23	Dynamic	-			0.79			0.71
24	Energetic				0.71			0.72
25	Bold				0.70			0.67
26	Determined				0.57			0.71
27	Strong	0.53			0.56			0.66
28	Confident				0.55			0.61
29	Motivated				0.53			0.71
30	Loud				0.49			0.55
31	Dedicated				0.48			0.69
32	Attractive					0.75		0.76
33	Feminine					0.75		0.67
34	Likeable					0.63		0.75
35	Smiling					0.62		0.64
36	Charismatic					0.49		0.61
37	Uncertain						0.79	0.69
38	Stressed						0.78	0.71
	Eigen Values	14.157	5.50	3.89	1.98	1.27	1.03	
	Percentage of Variance	37.26	14.47	10.24	5.20	3.33	2.70	
	Cumulative Percentage of Variance	37.26	51.73	61.97	67.16	70.50	73.20	

Examining the action units as listed in Table 5.6, we observe three results.

(1) Nose Wrinkle (AU 9) correlates positively with three leadership factors: *Intelligence*, *Tyranny* and *Dynamism*. Especially the correlation of Nose Wrinkle with *Tyranny* has a large effect size (0.52), which suggests that this facial expression is associated with a negative trait.

Table 5.5: Descriptive statistics for the six factors (N= 359)

Factors	No of items	Mean	SD	Skewness	Kurtosis	α
Intelligence	9	4.62	1.83	-0.14	-0.78	0.96
Sensitivity	7	5.19	1.72	-0.56	-0.32	0.94
Tyranny	6	4.71	1.83	0.02	-0.67	0.90
Dynamism	9	5.27	1.82	-0.39	-0.42	0.88
Likeability	5	5.64	1.85	-0.50	-0.32	0.85
Uncertainty	2	3.87	1.63	0.32	-0.34	0.61

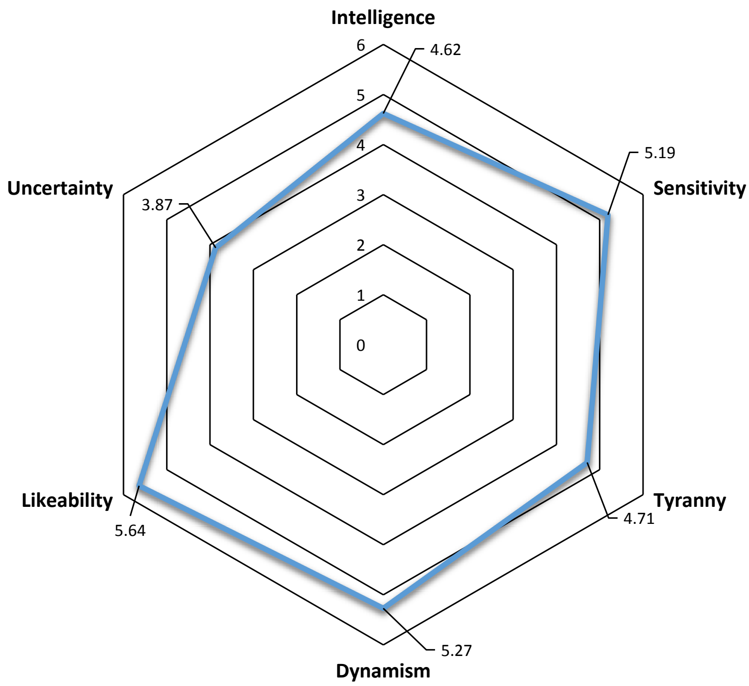

Figure 5.3: Radar plot of the mean factors resulting from the factor analysis on the ILT survey.

(2) In contrast, the facial expression of Dimpler (AU 14) has a medium to large effect size (0.4) and correlates negatively with both *Tyranny* and *Dynamism*.

(3) The facial expression Lids Tight (AU 7) correlates positively with *Sensitivity*, *Likeability*, and *Uncertainty* with an effect size that is larger than medium.

Table 5.6: Correlations of the 28 action units and 6 leadership factors. The p-values are given in parentheses. The correlations with p-values smaller than 0.05 are printed in boldface.

Factors	Intelligence	Sensitivity	Tyranny	Dynamism	Likeability	Uncertainty
(AU 1) Inner Brow Raise	0.12 (0.51)	0.06 (0.74)	-0.03 (0.88)	-0.01 (0.97)	-0.04 (0.84)	0.00 (0.98)
(AU 2) Outer Brow Raise	-0.03 (0.85)	-0.09 (0.63)	0.16 (0.37)	0.09 (0.63)	-0.05 (0.79)	-0.11 (0.53)
(AU 4) Brow Lower	0.08 (0.66)	0.19 (0.30)	-0.19 (0.28)	0.03 (0.87)	0.08 (0.64)	0.11 (0.53)
(AU 5) Eye Widen	**-0.38 (0.03)**	-0.17 (0.35)	-0.14 (0.42)	-0.12 (0.51)	-0.08 (0.68)	-0.23 (0.19)
(AU 9) Nose Wrinkle	**0.35 (0.04)**	0.20 (0.26)	**0.52 (0.00)**	**0.45 (0.01)**	0.24 (0.18)	0.14 (0.44)
(AU 10) Lip Raise	-0.33 (0.06)	-0.17 (0.33)	-0.12 (0.51)	-0.14 (0.43)	-0.13 (0.47)	0.09 (0.63)
(AU 12) Lip Corner Pull	-0.20 (0.26)	0.02 (0.93)	-0.21 (0.24)	-0.17 (0.36)	0.06 (0.73)	0.18 (0.32)
(AU 14) Dimpler	-0.22 (0.21)	-0.14 (0.44)	**-0.42 (0.02)**	**-0.40 (0.02)**	-0.22 (0.22)	0.09 (0.62)
(AU 15) Lip Corner Depressor	0.02 (0.93)	-0.20 (0.27)	0.11 (0.55)	-0.11 (0.53)	-0.20 (0.27)	-0.04 (0.81)
(AU 17) Chin Raise	-0.01 (0.98)	-0.26 (0.14)	0.03 (0.87)	-0.10 (0.56)	-0.23 (0.21)	**-0.35 (0.04)**
(AU 20) Lip stretch	0.19 (0.29)	0.26 (0.14)	0.09 (0.63)	0.26 (0.15)	0.30 (0.09)	0.02 (0.90)
(AU 6) Cheek Raise	0.00 (0.98)	0.21 (0.23)	0.02 (0.93)	0.08 (0.68)	0.29 (0.10)	0.26 (0.15)
(AU 7) Lids Tight	0.24 (0.17)	**0.38 (0.03)**	0.13 (0.46)	0.21 (0.24)	**0.37 (0.03)**	**0.44 (0.01)**
(AU 18) Lip Pucker	-0.00 (0.98)	-0.18 (0.33)	-0.12 (0.51)	-0.20 (0.26)	-0.26 (0.15)	-0.10 (0.60)
(AU 23) Lip Tightener	-0.17 (0.35)	-0.33 (0.06)	-0.05 (0.77)	-0.15 (0.41)	-0.32 (0.07)	-0.32 (0.07)
(AU 24) Lip Presser	-0.21 (0.24)	-0.34 (0.06)	-0.09 (0.61)	-0.18 (0.31)	-0.34 (0.05)	-0.20 (0.27)
(AU 25) Lips Part	0.28 (0.12)	0.30 (0.09)	0.20 (0.28)	0.34 (0.06)	0.33 (0.06)	0.05 (0.76)
(AU 26) Jaw Drop	0.06 (0.73)	0.17 (0.35)	0.17 (0.35)	0.15 (0.41)	0.24 (0.18)	0.25 (0.16)
(AU 28) Lips Suck	-0.10 (0.57)	0.00 (0.98)	-0.27 (0.12)	-0.20 (0.25)	-0.10 (0.59)	0.27 (0.13)
(AU 45) Blink/Eye Closure	0.05 (0.78)	-0.04 (0.81)	0.19 (0.29)	0.05 (0.78)	-0.01 (0.96)	0.08 (0.65)
Fear Brow (1+2+4)	0.20 (0.26)	0.12 (0.51)	0.18 (0.30)	0.19 (0.29)	0.09 (0.64)	0.11 (0.56)
Distress Brow (1 1+4)	0.18 (0.31)	0.14 (0.45)	0.20 (0.25)	0.22 (0.21)	0.10 (0.56)	0.13 (0.47)

5.4 DISCUSSION

Our study relied on completely different (and more natural) data than the study by Trichas and Schyns (2012). All in all, we found 6 factors. The factors cover similar items as those found by Trichas and Schyns (2012). This is quite striking, given the fact that our participants (first-year undergraduate students) differed from those of Trichas and Schyns (2012) in their experiment 3 (Cypriot bank employees). It indicates that the ILT survey consistently captures leadership traits across considerable different presentations of leadership. Our correlation analysis of the facial expressions and leadership factors revealed quite large correlations between action units and the leadership traits. The validity of these relations has to be established in future confirmatory studies. Yet, when taken together our findings suggest that there are *fine-grained* relations between the building blocks of facial expressions (facial action units) and leadership traits (as expressed in the 6 factors).

5.5 ANSWER TO RQ4

To the best of our knowledge, our study is the first to analyse directly the relation between facial expressions and leadership traits from (semi-)natural data. Although the limited number of participants in our study may have hampered the statistical power of our findings, our results point to the presence of a deep relation between the types of expressions and the occurrence of specific leadership traits (six leadership traits). Future work should aim at determining whether the relations found depend on the nature of the leadership contest or on the gender, age, and audience of the contestants.

Our results allow us to answer the research question *What is the relation of dynamic facial expressions to leadership assessment?* as follows. Dynamic facial expressions have a direct relation to the assessment of leadership in the sense that specific facial expressions such as Nose Wrinkle, Dimpler, and Lids Tight may have an effect on the assessment of leadership traits. Specifically, Nose Wrinkle and Dimpler have relatively large correlations with *Tyranny*, while Lids Tight is correlated to *Uncertainty*.

In more general terms, our results indicate that it is possible and feasible to develop evaluation and training software that provides direct feedback to individuals about their facial expressions of leadership.

6 GENERAL DISCUSSION

This thesis studied the power of facial expressions in a variety of competitive settings. It did so in order to answer the problem statement: what is the power of facial expressions in a competitive setting? To find an answer, we performed four studies on how facial expressions contribute to the assessments of contestants in competitions.

In the first study, described in Chapter 2, we investigated the contribution of facial expressions to attractiveness ratings of female pageants. We found that facial expressions contribute to the attractiveness ratings, but only when considered in combination with sexual dimorphism (femininity). The results suggest that the relevance of facial expressions of female faces is conditional on their attractiveness (as measured by femininity).

In the second study (Chapter 3), we determined the contribution of thin slices of male dynamic facial expressions to their assessment of attractiveness. The two findings are as follows. First, attractiveness ratings of male faces in static or dynamic form are highly correlated, but differ in their absolute value. Male dynamic faces are assessed to be slightly more attractive than male static faces. Second, our findings suggests that thin slices of dynamical facial expressions may contribute to the attractiveness. On average, less mouth movements correlate with higher attractiveness ratings.

In the third study (Chapter 4), we investigate the contribution of facial expressions in identifying the winner of musical contests. Our research showed that facial expressions allow for the identification of the winning musician to an extent that almost matches the performance of novice or expert human participants.

In the fourth study (Chapter 5), we investigated the relation of dynamic facial expressions to leadership assessment. We found that specific dynamic facial expressions seem to relate to the assessment of leadership traits.

In what follows, we discuss the strengths of our study (section 6.1) and the points of improvement (section 6.2). Finally, we relate our findings to recent work on the power of facial expressions (section 6.3).

6.1 STRENGTHS OF THE STUDY

We have identified several relations between the building blocks of facial expressions (facial landmarks and facial action units) and the assessment of qualities of relevance to a competition. The findings of our exploratory studies provide claims for future confirmatory studies. Below, we list four findings which may give rise to such claims.

- Facial expressions contribute to attractiveness ratings of females, conditional on sexual dimorphism (average femininity).

- Dynamical facial expressions contribute to attractiveness of males.
- Facial expressions support the prediction of the winning musician in a competitive context.
- There seems to be a relation between specific facial expressions and leadership traits.

Taken all our results together, the findings may guide us to formulate relevant claims for future research.

6.2 POINTS OF IMPROVEMENT

Our four studies suffered from three types of shortcomings which we identify as points of improvement. The three points of improvement are : (1) the statistical power of our correlation studies (see 6.2.1), (2) the sample sizes used (see 6.2.2), and (3) the validity of facial expression measurements (see 6.2.3).

6.2.1 Statistical Power of Correlation Analyses

In our four exploratory studies we reported the results of correlation analyses. In reporting them, we defined a "rather arbitrary" threshold of $p = 0.05$. We selected the value to highlight some correlations which may be reflecting a real correlation, rather than a spurious one. However, as stated in the different Chapters, the possibility that the obtained correlations are spurious still exists. A confirmatory analysis of our findings with the opportunity of determining statistical significance would require multiple comparison methods to compensate for the inflation of "significant" p-values. It means that the correlation results obtained as a result of exploratory studies, should only be used as guidelines for follow-up studies in particular for the formulation of testable hypotheses. To improve the statistical power of correlation analyses, larger sample sizes are required.

6.2.2 Sample Sizes

In the four studies described in the thesis, the sample sizes were relatively small. In Chapter 2, we relied on data extracted from 127 videos. In Chapter 3, 46 videos were used. Chapter 4 featured 10 competitions only. Chapter 5 relied on 33 videos. As is well known, small sample sizes limit the power of statistical analyses. Therefore, it will be beneficial to increase the sample sizes of studies like ours.

6.2.3 Validity of the Facial Expression Measurements

Current methods for the automatic coding of facial expressions (such as CERT) are not perfect. The inevitable imperfections translate into uncertainties in the results of our studies. The technology underlying the automatic coding of facial expressions is being improved continuously. Hence, using a state-of-the-art version of facial expression coding is an important point of improvement. We believe that future research will greatly benefit from the recent technological progress associated with deep learning (Kaya, Gürpınar & Salah, 2017).

What have we learned from our study of the power of facial expressions in competitive settings? What are the advances that we have made on understanding the power of facial expressions? Our examination of three types of contests, i.e., beauty contest, musical contest, and leadership contest, gave rise to specific insights into the effects of facial expressions on the successful performances in contests. Our findings suggest that facial expressions provide cues to estimate the success in a contest. What we have not investigated is what causes the cues to be useful. It may be that specific display rules underlie the predictive power of facial expressions. Winners tend to exhibit certain types of facial expressions and therefore judges tend to favour those contestants who tend to have the facial expressions of a winner. In our study of piano finalists, the fact that facial expressions on its own could predict the winner of the musical contest may be explained in this way. Whatever the cause of the facial-expression cues, it is clear that our studies revealed the importance of facial expressions in assessing the winner in a variety of contests. The main advance that our study has made is that the facial cues are subtle and not always clearly related to a single facial action unit. In the light of recent studies that emphasise the combination of multiple non-verbal cues (see, e.g., Schirmer & Adolphs, 2017), i.e., facial expressions, vocal expressions, gestures, posture, body movements, and gait, we expect that combining facial cues with other types of non-verbal cues offers the potential to create powerful predictive algorithms that can be used for training contestants and predicting contest outcomes.

6.3 RELATING THE FINDINGS TO RECENT WORK

Now we know that our findings are able to answer our problem statement (see chapter 7), we consider other recent work on the trends they communicate to us. So our point of departure is that facial expressions do contribute to the assessment of the winner of a competition. A rather recent work that is of general relevance to our research approach, such as Biel et al. (2012), has already predicted personality traits using fully automatic facial expressions. They applied automatic facial expression recognition to process a sample of vlogs collected from YouTube and detected the presence of facial expressions by means of a hidden Markov model method. The results indicated that facial expressions allow for the prediction of the personality trait of extraversion. In line with this finding, our study collected video data from YouTube about competitions and contests, in an attempt to obtain insightful cues of the human facial expressions of winners. Our findings assure that facial expressions have the power to predict the assessments of contestants.

In what follows, we discuss recent works in relation to our four studies.

First, in the attractiveness study (study 1, Chapter 2), we found that a combination of sexual dimorphism and facial expressions is effective since they contribute together to attractiveness ratings. A recent study addressing the relation between facial attractiveness and health in humans, confirmed that male attractiveness is predicted by masculinity and female attractiveness by femininity (Foo, Simmons & Rhodes, 2017). The conditional impact of facial expressions on attractiveness ratings may be of relevance for the emerging field of the social psychophysics of face communication (see Jack & Schyns, 2017). Social Psychophysic studies the face as a tool for social communication. Apart from deepening our understanding of the foundations of human attractiveness, in the context of the social psychophysics of face communication, our findings may support the development of attractive and effective embodied conversational agents to realise future human computer interfaces.

Second, in study 2, we found a slight advantage of dynamic stimuli as compared to static stimuli. In addition, male mouth movements had a negative effect on attractiveness ratings. Recently, Rymarczyk, Żurawski, Jankowiak-Siuda and Szatkowska (2016) found that the degree of facial mimicry depends on the use of static versus dynamic stimuli. In their study, they focussed on the impact of dynamic facial expressions on judgements of emotional intensity and on degree of facial mimicry. Emotional intensity was measured by means of a survey. Facial mimicry was recorded by measuring participant's facial muscle activity. In the study, the participants were given static and dynamic stimuli of happy or angry faces. The results revealed that dynamic expressions were perceived as being more emotionally intense than static ones. Dynamic displays of happiness evoked a stronger muscular activity, which suggests that subjects expressed positive emotion through mimicry.

As for the negative contribution of mouth movements, the recent study by Racca et al. (2016) may be of relevance. Racca et al. (2016) conducted a study to determine qualitative differences in the facial expressions of males and females. They instructed 18 students (9 female, 9 male) to perform a perceptual task involving verbal answers. The researchers performed a detailed computational analysis of the facial dynamics (based on facial landmarks) of the female and male participants. They found typical temporal patterns associated with mouth movements for females, but not for males. These findings point at gender-specific mouth dynamics that should be taken into account when explaining the role of dynamic facial expressions in attractiveness ratings of females and males.

Third, in our prediction of the winning finalists (study 3), we found that the prediction of the winner is possible on the basis of visual cues only. A recent study by Vuoskoski, Gatti, Spence and Clarke (2016) investigated how the mode of presentation of musical performances (audio-only, visual-only, or audiovisual) affects the emotional responses of participants. The emotional response was measured by means of galvanic skin response and heart rate. Vuoskoski et al. (2016) found that the emotional response was highest in the audio-only mode of presentation. These findings suggest that the prediction of the winner on the basis of visual cues may not be based on emotional cues, but rather on emotionally neutral information extracted from the video sequence.

Fourth, in our investigation of the relation between facial expressions and leadership (study 4), we found the suggestion that specific facial expressions are associated with perceived leadership traits. A recent review of research on charisma and embodiment (Reh, Susan, Niels & Steffen, 2017), proposes a novel framework for studying charisma and leadership in which the emphasis is on bodily contact (e.g., a pad on the shoulder or a friendly touch) and on social nonverbal signals, such as facial expressions. Our exploratory findings fit nicely into this new framework for studying leadership, by suggesting relations between facial expressions and the perception of leadership.

All in all, all our studies seem to connect quite well to recent developments. Thus, we were able to complete our research in chapter 7 by answering the PS and the four RQs as well as to suggest directions for future research.

7 CONCLUSIONS AND FUTURE RESEARCH

In this chapter we present the final conclusions of our research. In section 7.1 we start providing answers to the four research questions that we set out to investigate at the beginning of our study. Then, we provide our answer in the light of the problem statement in section 7.2. Moreover, we formulate our main conclusions. Finally, we discuss future applications in section 7.3.

7.1 ANSWERS TO THE FOUR RQS

In subsection 1.5, we formulated four research questions. We addressed these research questions in the chapters 2, 3, 4 and 5. In this section, we summarise our answers on the four RQs.

Answer to RQ1

In chapter 2 we aimed at discovering the contribution of facial expressions of female pageants to the rating of their attractiveness. Our first research question read as follows.

RQ1: *To what extent do facial expressions contribute to the attractiveness ratings in relation to femininity?*

To answer RQ1, we reviewed various existing studies. We described a range of findings on facial attractiveness. Specifically, we found literature that suggested to measure attractiveness by means of facial expression analysis software. We collected video data from 127 females of the Miss World 2013 competition. We ran computational experiments on the video sequences which were automatically coded in facial expressions. The main result of our study provides a clear answer to RQ1: Facial expressions contribute to the attractiveness ratings but only when considered in combination with sexual dimorphism (femininity).

Answer to RQ2

Chapter 3 focussed on the contribution of dynamic information (videos) as compared to static information (images) in the assessment of facial attractiveness. Our second research question was formulated as follows.

RQ2: *To what extent do thin slices of dynamic facial expressions contribute to the attractiveness of males?*

To answer RQ2, we examined the relevant literature on the assessment of static and dynamic expressions of attractiveness. We found that there was some disagreement on the existence of a difference in the attractiveness ratings for static and dynamic faces. The disagreement could not be explained by the gender of the to-be-assessed model. We performed survey analyses to determine the correlation between static and dynamic male faces and their ratings for male attractiveness in 46 thin slices extracted from Mister World 2013 video presentations. Further, we determined which type of dynamic information in facial stimuli predicted the attractiveness ratings. We performed computational analyses by examining the dynamics of facial landmarks and head pose in terms of dynamic features. This allowed us to answer RQ2 as follows.

First, in the survey study our findings revealed that the attractiveness ratings of male faces in static or dynamic formats are highly correlated. However, the attractiveness ratings do differ in an absolute sense. Male dynamic faces are assessed to be slightly more attractive than male static faces. Second, in the computational study, thin slices of dynamical facial expressions contribute to the attractiveness of males in a positive way and in a negative way. The positive contribution is that, on average, presenting a male face in a dynamic way leads to a slight increase in attractiveness rating (0.25 point on a 7-point scale). The negative contribution is that, the amount of mouth movements correlate negatively with attractiveness ratings. These answers may be translated into two recommendations for male pageants: (1) they should present themselves as much as possible in a dynamic fashion (i.e., through video or live appearances), and (2) they should limit their mouth movements as much as possible.

Answer to RQ3

Tsay (2013) studied the identification of a winning musician by sight only. She prompted us to state the following research question.

RQ3: *To what extent do facial expressions allow for the identification of winning musicians?*

Our experimental results revealed that facial expressions allow for the identification of the winning musician at a level that comes close to the performances of novice and expert human participants. The findings suggest that facial expressions to a large extent contribute to the visual identification of winners of a musical contest.

Answer to RQ4

Prompted by a recent study, we adopted Implicit Leadership Theory (ILT) to guide us in studying the relation between facial expressions and the assessment of leadership. We formulated our fourth research question as follows.

RQ4: *What is the relation of dynamic facial expressions to leadership assessment?*

We answer RQ4 as follows. We found that dynamic facial expressions have a direct relation to the assessment of leadership in the sense that specific facial expressions correlate with the assessment of leadership traits.

7.2 ANSWER TO THE PROBLEM STATEMENT

Our study examines the extent to which facial expressions have power in a competitive setting. Based on the study we formulated our problem statement (PS) as follows.

Problem Statement (PS): *What is the power of facial expressions in a competitive setting?*

With reference to the answers to the four research questions, we arrived at the following answer given in four points.

1. Facial expressions contribute to determine the outcome of a competition. Hence, the power of facial expressions in competitive settings is confirmed.
2. Facial expressions can be assessed both by static and dynamic characteristics. Both static and dynamic facial cues contribute to the power of facial expressions.
3. Facial expressions of the finalists of a competition provide cues to predict who will be the winner.
4. Specific facial expressions may contribute to the assessment of leadership traits.

Given our findings, the power of facial expressions in a competitive setting is considerable. They may affect the outcome of a competition, whether it concerns an attractiveness contest, a musical contest, or a leadership contest.

All in all, we may conclude that the power of facial expressions in a competitive setting should be taken into account when trying to predict the most likely winner.

7.3 FUTURE RESEARCH

Our exploratory analysis of the power of facial expression provided putative relations between facial expressions and human assessments of attractiveness, performance, and leadership. Future analysis should follow up on these results by scaling the data sets. For the attractiveness studies this would imply extending the number of Miss World and Mister World competitions included in the dataset. It would allow for distinguishing contest-specific from universal effects of facial expressions on attractiveness assessments. Similarly, for the musical performances, the extension of the number of piano competitions in the dataset would strengthen the statistical validity of our findings. Including other musical competitions (e.g., singing and other instruments), would help to differentiate between instrument-specific and universal contributions. For the leadership study, increasing the number of data samples to include both males and females in a wide variety of settings would yield the analogous benefits.

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Appendices

The section Appendices contains ten appendices. They are listed below:

A. Facial Action Coding Systems (FACS) and the 7 Basic Emotions 2013

B. The Ranks and Scores of the Miss World 2013 and the Judges

C. URLs of the Miss World 2013 Profile Videos

D. Attractivenes Ratings of Mister World 2014 (Static Thin Slices)

E. URLs of the Mister World 2014 Profile Videos

F. URLs of the Piano Competition Videos

G. URLs of the JKT48 Profiles Videos

H. JKT48 Video Ratings

I. JKT48 Qualtrics Survey

J. List of the ILT Factors and the ILT Items

A FACIAL ACTION CODING SYSTEMS (FACS) AND THE 7 BASIC EMOTIONS

The pictures are reproduced from https://www.cs.cmu.edu/ face/facs.htm [8], except for picture AU45, Fear Brow, and Distress Brow. The picture of AU45 is taken from Brefczynski-Lewis, Berrebi, McNeely, Prostko and Puce (2011). The Fear Brow and Distress Brow images are taken from Alam, Barrett, Hodapp and Arndt (2008).

Table A.1: Single action units (AU) in the Facial Action Coding System

AU	Descriptor	Muscular	Picture
1	Inner Brow Raise	Frontalis, Pars Medialis	
2	Outer Brow Raiser	Frontalis, Pars Lateralis	
4	Brow Lowerer	Depressor Glabellae, Depressor Suprecilli; Corrugator	
5	Eye Widen	Levator Palpebrae Superioris	
6	Cheek Raise	Orbicularis Oculi, Pars Orbitalis	
7	Lid Tight	Orbicularis Oculi, Pars Palebralis	
9	Nose Wrinkler	Levator Labii Superioris, Alaeque cap Nasi	
10	Upper Lip Raise	Levator Labii Superioris, Caput Infraorbitalis	

8 https://www.cs.cmu.edu/ face/facs.htm

Table A.1 (*Continued*)

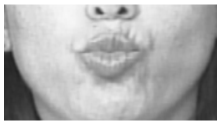
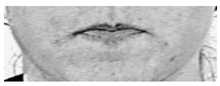
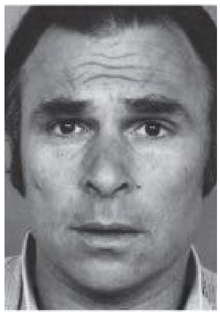
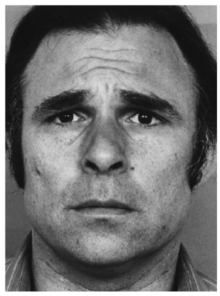
AU	Descriptor	Muscular	Picture
12	Lip Corner Pull	Zygomatic Major	
14	Dimpler	Buccinator	
15	Lip Corner Depressor	Triangularis	
17	Chin Raiser	Mentalis	
18	Lip Pucker	Incisivii Labii Superioris; Incicivii Labii Inferioris	
20	Lip Stretch	Risorius	
23	Lip Tightener	Orbicularis Oris	
24	Lip Presser	Orbicularis Oris	
25	Lips Part	Depressor Labii, or Relaxation of Mentalis or Orbicularis Oris	

Table A.1 (*Continued*)

AU	Descriptor	Muscular	Picture
26	Jaw Drop	Masetter; Temporal and Internal Pterygoid Relaxed	
28	Lip Suck	Orbicularis Oris	
45	Blink/Eye Closure	Relaxation of Levator Palpebrae Superioris	
(1+2+4)	Fear Brow		
(1,1+4)	Distress Brow		

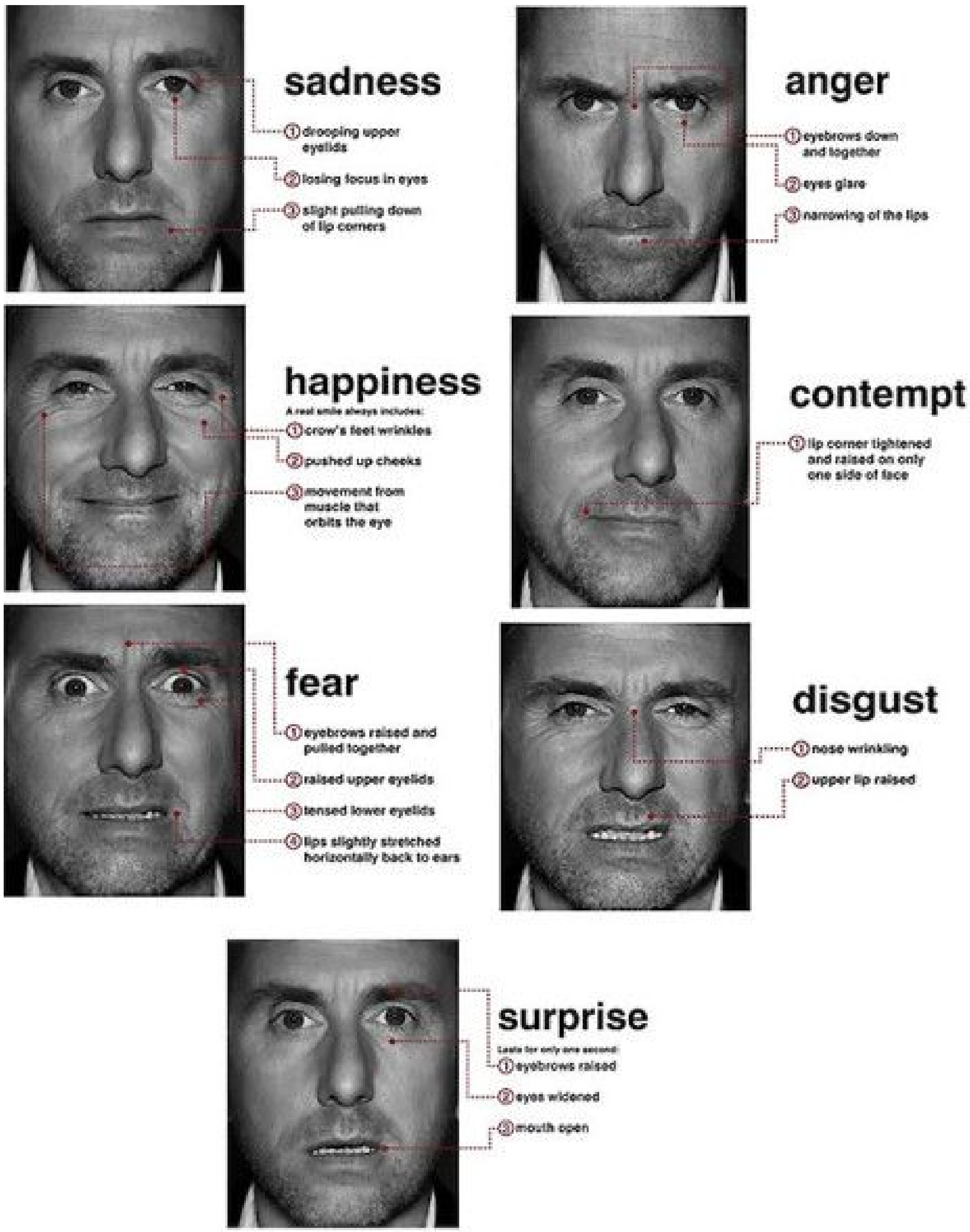


Figure A.1: .
Seven Basic Emotions. The pictures are reproduced from Pinterest (https://www.pinterest.com/pin/212161832425357040/)

B THE RANKS AND SCORES OF THE MISS WORLD 2013 AND THE JUDGES

Appendix B provides the scores of the Miss World 2013 contest, as assessed by seven judges. The first column of the table lists the countries. The next seven columns lists the scores given by the judges (A to G). The final column provides the scores averaged over the seven judges (table B.1). Seven judges of Miss World 2013 contest (table B.2)

Table B.1: The ranks and scores of the Miss World 2013 contest

Rank	Countries	Judge A	Judge B	Judge C	Judge D	Judge E	Judge F	Judge G	Avg. Sc.
1	Philippines	4.47	5.00	4.62	4.99	5.00	5.00	4.60	4.81
2	Brazil	4.73	4.51	4.39	4.92	5.00	5.00	4.75	4.76
3	Spain	4.34	5.00	4.64	4.94	5.00	4.50	4.65	4.72
4	France	3.84	4.50	4.10	4.98	5.00	5.00	4.45	4.55
5	Ukraine	3.28	4.51	3.78	4.88	4.75	5.00	4.78	4.43
6	United States of America	4.18	4.51	4.00	3.70	4.50	4.20	4.50	4.23
7	India	3.77	4.00	3.70	4.30	4.50	3.80	4.73	4.11
8	Venezuela	4.18	4.00	3.20	4.45	4.50	4.00	4.39	4.10
9	South Africa	4.53	4.20	3.50	4.50	4.75	3.80	3.08	4.05
10	Jamaica	3.71	3.00	4.59	4.35	4.75	4.20	3.44	4.01
11	China	3.11	4.00	3.60	4.10	4.50	4.00	4.70	4.00
12	Italy	2.23	4.50	4.26	4.10	4.50	4.00	4.27	3.98
13	Japan	3.25	4.00	3.54	4.00	4.00	4.40	4.51	3.96
14	Australia	2.76	3.70	4.59	3.50	4.50	3.80	4.64	3.93
15	Puerto Rico	3.22	4.00	3.55	4.20	4.75	3.00	4.49	3.89
16	Ecuador	2.80	4.20	2.69	4.80	4.50	3.00	4.68	3.81
17	Denmark	3.02	3.50	3.79	3.40	4.50	4.00	4.40	3.80
18	Netherlands	2.84	4.00	4.19	4.30	4.50	2.80	3.84	3.78
19	Sri Lanka	2.50	4.00	3.60	4.30	4.50	4.00	3.54	3.78
20	Indonesia	3.48	3.00	3.50	4.45	4.50	3.80	3.69	3.77
21	Ghana	2.52	3.50	3.60	2.92	5.00	4.80	3.76	3.73
23	Mexico	3.99	4.00	3.00	3.80	4.00	3.60	3.51	3.70
24	Northern Ireland	3.06	3.00	3.35	3.70	4.50	3.80	4.47	3.70
25	Cote d'Ivoire	3.04	2.51	3.50	4.10	4.50	3.60	4.56	3.69
26	Kosovo	1.82	4.00	2.99	4.00	4.50	3.90	4.45	3.67
27	Lebanon	4.06	3.51	4.50	2.20	4.00	4.40	2.23	3.56
28	Cyprus	2.69	3.50	3.00	4.00	4.50	4.40	2.76	3.55
29	Albania	2.84	4.00	2.50	3.90	4.50	3.40	3.70	3.55
30	Georgia	1.86	4.00	3.65	2.80	4.00	3.80	4.45	3.51
31	Taiwan	2.68	4.00	2.50	3.95	4.50	3.90	2.95	3.50
32	Czech Republic	2.83	3.50	3.10	2.90	4.00	3.60	4.45	3.48
33	New Zealand	3.10	3.50	2.98	3.98	4.00	3.80	2.96	3.47
34	Gibraltar	2.56	3.50	2.30	4.15	4.50	3.70	3.54	3.46
35	Turkey	3.71	2.50	3.40	3.50	3.00	4.00	4.00	3.44
36	Poland	2.58	4.00	2.25	3.80	4.00	4.10	3.31	3.43

Table B.1 (*Continued*)

Rank	COUNTRY	Judge A	Judge B	Judge C	Judge D	Judge E	Judge F	Judge G	Avg.
37	Malaysia	1.83	4.00	2.65	3.88	4.50	3.50	3.65	3.43
38	Guinea	2.66	2.50	2.60	4.00	4.50	3.80	3.70	3.39
39	Norway	2.50	3.51	3.51	3.60	3.50	3.50	3.62	3.39
40	Guyana	2.23	1.51	3.50	4.70	4.75	4.50	2.53	3.39
41	South Sudan	2.95	2.00	3.00	3.80	4.50	4.00	3.40	3.38
42	Slovenia	2.61	4.50	2.60	3.50	3.50	3.30	3.55	3.37
43	Scotland	2.49	1.51	3.76	3.90	4.00	3.70	4.11	3.35
44	Hungary	3.36	2.50	3.29	3.95	4.00	2.90	3.35	3.34
45	Peru	2.91	3.50	3.30	3.15	4.00	3.00	3.47	3.33
46	Martinique	2.74	3.00	2.99	3.40	3.50	3.90	3.50	3.29
47	Cameroon	2.61	2.50	4.20	3.00	4.50	3.70	2.33	3.26
48	England	3.29	4.00	3.50	3.50	3.00	3.00	2.54	3.26
49	Curacao	3.00	2.00	2.79	4.20	4.50	3.80	2.51	3.26
50	Belarus	2.88	3.51	2.20	2.80	4.00	4.00	3.33	3.25
51	Slovakia	2.29	2.50	3.30	3.70	3.50	3.60	3.53	3.20
52	Moldova	1.99	2.51	2.99	3.95	4.50	4.20	2.23	3.20
53	Trinidad & Tobago	2.91	2.00	3.25	4.00	4.00	3.30	2.90	3.19
54	Kyrgyzstan	1.66	2.51	1.99	4.00	4.00	4.50	3.61	3.18
55	Bermuda	2.50	2.50	2.55	4.00	4.00	3.00	3.57	3.16
56	Ireland	2.83	2.50	2.80	3.20	3.00	2.70	4.49	3.07
57	Argentina	2.33	2.51	3.30	2.90	3.00	3.70	3.73	3.07
58	Bahamas	2.78	3.00	2.30	3.00	4.00	3.50	2.82	3.06
59	Vietnam	2.08	3.50	1.99	3.00	4.00	3.30	3.25	3.02
60	Dominica	1.98	1.50	3.55	3.50	4.00	3.90	2.59	3.00
61	Namibia	2.39	1.51	3.40	3.40	4.00	3.30	2.95	2.99
62	Greece	2.55	2.50	3.40	2.50	3.00	3.10	3.82	2.98
63	Paraguay	2.16	4.20	2.56	3.20	3.00	3.00	2.64	2.97
64	Thailand	2.16	2.51	1.99	4.20	4.00	2.60	3.25	2.96
65	Panama	1.87	4.00	3.70	1.90	3.00	2.80	3.39	2.95
65	Guatemala	3.14	3.51	1.50	2.70	3.00	3.30	3.46	2.94
66	Russia	2.18	3.00	3.35	3.40	3.00	2.50	3.15	2.94
67	Belize	2.77	3.00	2.35	2.50	4.00	3.40	2.55	2.94
68	Ethiopia	3.13	4.00	2.00	1.70	3.50	3.00	2.99	2.90
69	Dominican Rep	3.39	3.00	3.42	1.50	3.00	2.20	3.48	2.86
70	Bolivia	3.66	2.50	2.47	1.50	3.50	2.80	3.49	2.85
71	Tunisia	1.66	1.51	3.35	3.90	3.00	3.90	2.18	2.79
72	Bulgaria	2.15	3.50	1.69	3.00	3.50	2.50	2.80	2.73
73	Guadeloupe	2.63	2.50	3.40	1.80	2.50	3.70	2.59	2.73
74	Montenegro	2.33	3.00	3.60	1.50	3.00	2.70	2.85	2.71
75	Chile	1.74	3.50	2.50	2.00	3.50	2.80	2.93	2.71
76	Kazakhstan	1.55	2.00	2.19	2.50	3.50	2.80	4.40	2.71
77	Serbia	2.17	2.00	1.99	3.60	3.50	2.80	2.88	2.71
78	Lithuania	2.09	2.50	3.00	2.00	3.50	2.60	3.21	2.70
79	Wales	2.09	4.00	2.85	2.20	2.50	3.00	2.24	2.70
80	Croatia	2.35	1.51	3.40	2.20	3.00	3.30	3.00	2.68
81	Colombia	2.16	4.00	2.31	2.50	3.00	2.20	2.33	2.64

Table B.1 (*Continued*)

Rank	COUNTRY	Judge A	Judge B	Judge C	Judge D	Judge E	Judge F	Judge G	Avg. Sc.
82	Sweden	2.69	2.50	1.89	2.50	2.50	3.00	3.13	2.60
83	Uzbekistan	1.36	3.00	2.00	2.80	3.00	3.00	2.90	2.58
85	Botswana	2.01	2.00	3.20	2.20	2.50	3.10	2.64	2.52
86	Equatorial Guinea	2.29	2.00	2.00	3.15	2.50	2.80	2.91	2.52
87	Aruba	2.83	3.00	1.55	2.50	3.00	3.00	1.70	2.51
88	Haiti	1.61	3.50	1.99	2.85	2.50	3.30	1.77	2.50
89	Iceland	1.89	2.50	2.40	1.90	3.00	2.60	3.00	2.47
90	Nicaragua	2.09	2.00	1.90	2.00	4.00	2.10	3.12	2.46
91	Angola	3.11	2.50	2.33	1.70	3.00	2.90	1.63	2.45
92	Costa Rica	1.92	2.00	1.89	2.80	3.50	2.30	2.68	2.44
93	Nepal	1.98	3.00	2.49	1.40	3.50	2.20	2.50	2.44
94	Bosnia & Herzogovina	2.43	2.00	1.90	1.70	3.50	2.50	3.00	2.43
95	Gabon	1.54	1.50	2.48	2.50	3.00	3.30	2.69	2.43
96	Belgium	2.21	2.50	3.40	1.50	2.50	2.80	2.10	2.43
97	Mongolia	1.84	2.60	1.80	1.50	2.50	3.00	3.37	2.37
98	US Virgin Islands	1.99	1.50	1.99	2.95	3.50	3.00	1.67	2.37
99	Malta	2.13	2.50	2.99	1.90	2.50	2.10	2.21	2.33
100	Hong Kong	1.80	2.50	1.77	2.20	2.50	3.20	2.34	2.33
101	Barbados	1.84	1.50	3.20	2.15	2.50	2.50	2.53	2.32
101	Austria	2.08	3.00	2.00	1.20	3.00	2.90	2.00	2.31
102	Romania	1.66	1.51	2.00	3.00	2.50	2.60	2.80	2.30
103	Uganda	1.17	2.51	2.20	2.20	2.50	2.70	2.75	2.29
104	Finland	2.94	1.50	1.95	2.70	2.50	2.10	2.22	2.27
105	Kenya	1.98	3.00	2.63	1.20	2.50	2.80	1.79	2.27
106	Samoa	1.49	1.51	2.50	2.80	2.50	3.00	2.00	2.26
107	British Virgin Islands	1.78	1.50	2.60	1.95	2.50	2.70	2.48	2.22
108	Nigeria	1.77	1.50	1.99	1.50	3.50	2.20	2.78	2.18
109	Germany	2.14	1.50	1.79	1.80	3.00	2.00	2.95	2.17
110	Switzerland	1.80	1.50	1.99	2.10	2.50	2.20	2.95	2.15
111	Tanzania	1.57	1.50	1.99	2.90	3.00	2.40	1.65	2.14
112	Canada	1.50	1.50	2.60	1.45	4.00	2.20	1.70	2.14
113	Macedonia	1.81	2.50	2.00	1.40	2.00	2.40	2.80	2.13
114	Latvia	2.04	2.00	2.15	1.40	2.50	2.80	1.63	2.07
115	Singapore	1.33	1.51	2.30	1.40	2.50	2.20	2.95	2.03
116	Portugal	2.00	1.51	1.50	1.40	3.50	2.50	1.65	2.01
117	Korea	1.88	1.51	1.99	1.80	2.00	2.30	2.55	2.00
118	Saint Kitts and Nevis	1.58	1.50	1.99	1.80	3.00	2.20	1.90	2.00
119	Mauritius	1.54	1.51	1.99	1.70	2.50	2.60	2.09	1.99
120	Seychelles	1.99	1.51	1.79	1.90	2.50	2.50	1.70	1.98
121	Fiji	1.43	1.50	1.59	2.00	2.00	2.30	2.47	1.90
122	El Salvador	1.58	2.00	1.99	1.50	2.50	2.00	1.59	1.88
123	Honduras	1.09	3.00	1.55	1.25	2.00	2.00	2.15	1.86
124	Guam	1.70	2.50	1.50	1.15	1.50	2.10	2.54	1.86
125	Guinea-Bissau	1.00	1.50	1.99	1.40	2.50	2.50	1.60	1.78
126	Zambia	1.51	1.50	1.50	1.35	1.50	2.00	2.43	1.68
127	Lesotho	1.06	2.50	1.59	1.35	1.50	2.00	1.61	1.66

Table B.2: Seven Judges of Miss World 2013

Judges (A to G)	Country	Beauty Agency	Occupation
Donald West	Canada	Pageantopolis	Photographer and Videographer
Ricardo Guilardes	Chile	Chilean Charm	Press Photographer
Jimmy Harris	United States	Beauty School	Director
Edwin Dominguez	Panama	Global Beauties	Director
Nur Soegijatno	Indonesia	Indonesia Pageants	Director
Andre Sleigh	South Africa	Eye of Beauty	Director
Edwin Toledo	Puerto Rico	Beauty Institution	Director

C URLS OF THE MISS WORLD 2013 PROFILE VIDEOS

Appendix C provides the URLs of the Miss World 2013 profile videos used for analysis in the study. The table C.1 is alphabetically sorted by country.

Table C.1: URLs of the Miss World 2013 profile videos

No	Countries	Youtube URLs
1	Albania	https://www.youtube.com/watch?v=2ENXNklmBJ4&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=
2	Angola	https://www.youtube.com/watch?v=90XDhbKXkLk&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=2
3	Argentina	https://www.youtube.com/watch?v=Ou4KWTT4lRo&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=3
4	Aruba	https://www.youtube.com/watch?v=dT7kXaZPHOo&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=
5	Australia	https://www.youtube.com/watch?v=f7ryYoCY5Bc&index=5&list=
6	Austria	https://www.youtube.com/watch?v=9EiJE4mLDG8&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=6
7	Bahamas	https://www.youtube.com/watch?v=HoN2EhK4ELA&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=7
8	Barbados	https://www.youtube.com/watch?v=p-S6uNbOblg&index=8&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA
9	Belarus	https://www.youtube.com/watch?v=7penDO99Ucg&index=9&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA
10	Belgium	https://www.youtube.com/watch?v=tS9fc1mgG6M&index=10&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA
11	Belize	https://www.youtube.com/watch?v=pPEDNyRX5Tk&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=11
12	Bermuda	https://www.youtube.com/watch?v=r2_hgarbnrI&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=12
13	Bolivia	https://www.youtube.com/watch?v=5F89XAH3KBw&index=13&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA
14	Bosnia	https://www.youtube.com/watch?v=bm-Kkrvb4Wk&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=14
15	Botswana	https://www.youtube.com/watch?v=KkN2Lz7jkSM&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=15
16	Brazil	https://www.youtube.com/watch?v=DSdu-N_jVDc&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=16
17	British Virgin	https://www.youtube.com/watch?v=V1rZXSLt-LI&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=17
18	Bulgaria	https://www.youtube.com/watch?v=hPC4RAWMEeA&index=18&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA
19	Cameroon	https://www.youtube.com/watch?v=n6zPscq8z1Q&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=19
20	Canada	https://www.youtube.com/watch?v=48fCkw5LPzw&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=20
21	Chile	https://www.youtube.com/watch?v=JSUavvk-sbs&index=21&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA
22	China PR	https://www.youtube.com/watch?v=YIu-9x4v9kM&index=22&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA
23	Chinese Taipei	https://www.youtube.com/watch?v=YECsg5f4px4&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=23
24	Colombia	https://www.youtube.com/watch?v=wtnm1RR8lJg&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=24
25	Costa Rica	https://www.youtube.com/watch?v=sN4om2zgEWA&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=
26	Cote D'Ilvore	https://www.youtube.com/watch?v=7hg5pAAf5t8&index=26&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA
27	Croatia	https://www.youtube.com/watch?v=22PSJ87xamg&index=27&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA
28	Curacao	https://www.youtube.com/watch?v=Oe6rBJmtn6E&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=28
29	Cyprus	https://www.youtube.com/watch?v=sDFC5rIxCy8&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=29
30	Czech Republik	https://www.youtube.com/watch?v=ttTMobtUQLk&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=30
31	Denmark	https://www.youtube.com/watch?v=GNC-hdVk8kE&index=31&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA
32	Dominica	https://www.youtube.com/watch?v=y3AsQPRMBq8&index=32&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA
33	Ecuador	https://www.youtube.com/watch?v=AWbd9U86Z-A&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=34
34	El Salvador	https://www.youtube.com/watch?v=-s_J6dGbhkQ&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=35
35	England	https://www.youtube.com/watch?v=EAkQIkfqYZg&index=36&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA
36	Equatorial Guinea	https://www.youtube.com/watch?v=I6H8O2DqePQ&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=37
37	Ethiopia	https://www.youtube.com/watch?v=xkHTNg9onKs&index=38&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA
38	Fiji	https://www.youtube.com/watch?v=FVS_QEmsuZI&index=39&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA

Table C.1 (*Continued*)

No	Countries	Youtube URLs
39	Finland	https://www.youtube.com/watch?v=zjf_62HYgxo&index=40&list=
40	France	https://www.youtube.com/watch?v=e8solveSpJQ&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=41
41	Gabon	https://www.youtube.com/watch?v=iVX1ldGUsfo&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=42
42	Georgia	https://www.youtube.com/watch?v=LuikK84q8hI&index=43&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA
43	Germany	https://www.youtube.com/watch?v=oOoFG4rFh-c&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=44
44	Ghana	https://www.youtube.com/watch?v=VcswVHPJkCE&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=
45	Gibraltar	https://www.youtube.com/watch?v=po6D-C7l7Zo&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=46
46	Greece	https://www.youtube.com/watch?v=DvGdMjtS788&index=47&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA
47	Guadeloupe	https://www.youtube.com/watch?v=V75IELPVx8I&index=48&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA
48	Guam	https://www.youtube.com/watch?v=BCRqToyWcAo&index=49&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA
49	Guatemala	https://www.youtube.com/watch?v=U-uzOeeTN8g&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=50
50	Guinea	https://www.youtube.com/watch?v=f-YZ3QWWJeU&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=51
51	Guinea-Bissau	https://www.youtube.com/watch?v=9vqw1rgmVCU&index=52&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA
52	Guyana	https://www.youtube.com/watch?v=vPejAoaWKSQ&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=53
53	Haiti	https://www.youtube.com/watch?v=Q1Gpj1yUbNs&index=54&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA
54	Honduras	https://www.youtube.com/watch?v=qxHxKfPRjmY&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=55
55	Hongkong China	https://www.youtube.com/watch?v=QgmZSuoTZVA&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=56
56	Hungary	https://www.youtube.com/watch?v=cW2oy-qzQgc&index=57&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA
57	Iceland	https://www.youtube.com/watch?v=8eWCFmyRxNo&index=58&list=
58	India	https://www.youtube.com/watch?v=XqfCCluD5LQ&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=59
59	Indonesia	https://www.youtube.com/watch?v=BWofttzGvro&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=60
60	Ireland	https://www.youtube.com/watch?v=H3qqeCGENoA&index=61&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA
61	Italy	https://www.youtube.com/watch?v=65mmdmsLTos&index=62&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA
62	Jamaica	https://www.youtube.com/watch?v=b47Pu-GXUUQ&index=63&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA
63	Japan	https://www.youtube.com/watch?v=HVAuEtIzXvM&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=64
64	Kazakhstan	https://www.youtube.com/watch?v=qRNfWHmntmI&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=65
65	Kenya	https://www.youtube.com/watch?v=5c-EUBRZ_qA&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=66
66	Korea	https://www.youtube.com/watch?v=aEkoZKNTskk&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=67
67	Kosovo	https://www.youtube.com/watch?v=UHrLY8XlQcw&index=68&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA
68	Kyrgyztan	https://www.youtube.com/watch?v=zwoyYQO5k8Q&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=69
69	Latvia	https://www.youtube.com/watch?v=o6lWNADAaTw&index=70&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA
70	Lebanon	https://www.youtube.com/watch?v=h_HMJsK72hU&index=71&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA
71	Lesotho	https://www.youtube.com/watch?v=tJGzYUs4Haw&index=72&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA
72	Lithuania	https://www.youtube.com/watch?v=Q8FTYWa5qXQ&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=73
73	Macedonia FYRO	https://www.youtube.com/watch?v=MSRbY-9yXuY&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=74
74	Malaysia	https://www.youtube.com/watch?v=DYSp-CUH7fg&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=75
75	Malta	https://www.youtube.com/watch?v=IOap7aiommM&index=76&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA
76	Martinique	https://www.youtube.com/watch?v=YEg8X4B9NkI&index=77&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA
77	Mauritius	https://www.youtube.com/watch?v=GQYyDPoZ5oU&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=78
78	Mexico	https://www.youtube.com/watch?v=XOxuoxwmP5A&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=79
79	Moldova	https://www.youtube.com/watch?v=EnG2IA1Jo6E&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=80
80	Mongolia	https://www.youtube.com/watch?v=xeq7CtUGaHY&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=81
81	Montenegro	https://www.youtube.com/watch?v=3VEMlBq615E&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=82

Table C.1 (*Continued*)

No	Countries	Youtube URLs
82	Namibia	https://www.youtube.com/watch?v=n5yBJaZL_Dw&index=83&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA
83	Nepal	https://www.youtube.com/watch?v=CEj3L7xJvfg&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=84
84	Netherlands	https://www.youtube.com/watch?v=qvAN3sQAVeE&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=85
85	New Zealand	https://www.youtube.com/watch?v=a28a2z-20mk&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=86
86	Nicaragua	https://www.youtube.com/watch?v=0u5c0eyHHx0&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=87
87	Nigeria	https://www.youtube.com/watch?v=t8q9NlRnNb0&index=88&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA
88	Northern Ireland	https://www.youtube.com/watch?v=z0pzuxaCcq8&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=89
89	Norway	https://www.youtube.com/watch?v=6r0–pN-gX0&index=90&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA
90	Panama	https://www.youtube.com/watch?v=q19ulhCH3HQ&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=91
91	Paraguay	https://www.youtube.com/watch?v=_bBEAXaM04c&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=92
92	Peru	https://www.youtube.com/watch?v=ZDO-enZnl8I&index=93&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA
93	Phillipines	https://www.youtube.com/watch?v=tJzZxISX0-c&index=94&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA
94	Poland	https://www.youtube.com/watch?v=75ba499LwPc&index=95&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA
95	Portugal	https://www.youtube.com/watch?v=n29FOkmrWUk&index=96&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA
96	Puerto Rico	https://www.youtube.com/watch?v=3cwAyAWKu1Y&index=97&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA
97	Romania	https://www.youtube.com/watch?v=nDgOYyIOI_g&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=98
98	Russia	https://www.youtube.com/watch?v=XsyazjE9szU&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=99
99	Samoa	https://www.youtube.com/watch?v=GLxZ_TwKTNQ&index=100&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA
100	Scotland	https://www.youtube.com/watch?v=aUjWCY2AzpM&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=101
101	Serbia	https://www.youtube.com/watch?v=_qS_8GZl86A&index=102&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA
102	Seychelles	https://www.youtube.com/watch?v=VA7CWQNvRV4&index=103&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA
103	Singapore	https://www.youtube.com/watch?v=xkL4-ynDlzU&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=104
104	Slovakia	https://www.youtube.com/watch?v=_20ZIcYvFk8&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=105
105	Slovenia	https://www.youtube.com/watch?v=OgGB6kGcESc&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=106
106	South Sudan	https://www.youtube.com/watch?v=b8e9BYOhfxI&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=108
107	Spain	https://www.youtube.com/watch?v=Mzn-Ml1FZIk&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=109
108	Srilanka	https://www.youtube.com/watch?v=P084ewZC87E&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=110
109	St Kitts and Nevis	https://www.youtube.com/watch?v=R3QgChIiAOc&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=111
110	Sweden	https://www.youtube.com/watch?v=C58Bupt8t7w&index=112&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA
111	Switzerland	https://www.youtube.com/watch?v=LNsXfmEF02Q&index=113&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA
112	Tanzania	https://www.youtube.com/watch?v=wthrTRpP9sA&index=114&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA
113	Thailand	https://www.youtube.com/watch?v=dANjqZa4_VQ&index=115&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA
114	Trinidad and Tobago	https://www.youtube.com/watch?v=CqLZ4uz2HBQ&index=116&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA
115	Tunisia	https://www.youtube.com/watch?v=NcdP6QAc8rs&index=117&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA
116	Turkey	https://www.youtube.com/watch?v=uzQhkdFH8CM&index=118&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA
117	Uganda	https://www.youtube.com/watch?v=xKJyX9kTvUA&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=119
118	Ukraine	https://www.youtube.com/watch?v=IUxzSa2Iua0&index=120&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA
119	United States	https://www.youtube.com/watch?v=_-YB10GDJ00&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=121
120	US Virgin Islands	https://www.youtube.com/watch?v=_0j_tsGsnow&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=122
121	Uzbekistan	https://www.youtube.com/watch?v=Vp1BcqLbXNY&index=123&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA
122	Venezuela	https://www.youtube.com/watch?v=C1acPP4PAFg&index=124&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA
123	Vietnam	https://www.youtube.com/watch?v=0l4s_bnklmA&index=125&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA
124	Wales	https://www.youtube.com/watch?v=XYgQVICz6F0&index=126&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA
125	Zambia	https://www.youtube.com/watch?v=SOLp_xvuRbQ&list=PLU5UzgW959OAPrRZKtwgI1KRK6scw2tyA&index=127

D ATTRACTIVENESS RATINGS OF MISTER WORLD 2014 (THIN SLICES)

Appendix D provides the attractiveness ratings of the Mister World 2014 static and dynamic thin slices. The ratings for of static images in table D.1 and of dynamic images in table D.2.

Table D.1: Attractiveness ratings of Mister World 2014 (static thin slices)

Version	Age	Lebanon	Malta	Mexico	Moldova	Netherlands	Nigeria	Nireland	Paraguay	Peru	Philipines	Poland
1	26	3	1	5	2	6	2	1	1	3	5	2
1	20	5	1	5	3	6	1	2	2	2	4	2
1	19	2	3	5	3	6	3	1	5	3	4	2
1	22	1	2	5	1	7	2	2	2	4	5	3
1	19	3	3	6	3	6	2	5	2	5	6	2
1	25	2	3	6	3	5	4	4	3	5	5	5
1	18	3	4	6	4	6	2	3	2	5	3	2
1	20	5	6	6	4	6	4	4	4	5	6	3
1	22	3	2	6	3	2	2	5	2	3	5	1
1	21	5	5	6	4	7	3	6	4	5	4	4
1	20	3	1	5	2	7	1	2	2	4	4	1
1	23	4	3	6	3	6	3	5	2	4	2	4
1	21	2	2	5	3	4	3	2	2	3	5	5
1	22	4	2	7	2	5	4	2	2	3	-	1
1	20	5	3	5	2	5	3	3	3	2	3	4
1	20	5	4	6	3	7	4	5	4	5	4	4
1	18	2	3	3	3	6	2	2	1	4	2	6
1	23	2	4	6	1	6	4	5	3	5	3	3
1	19	3	3	6	3	6	5	5	2	2	4	3
1	27	1	1	1	1	3	1	1	1	1	1	1
1	20	1	1	5	1	5	1	3	2	2	3	3
1	19	3	5	7	2	7	2	5	2	6	3	4
1	21	3	3	5	2	6	2	4	4	2	2	3
1	18	1	2	3	2	7	1	1	2	2	4	2
1	18	5	3	6	2	7	1	2	3	2	3	2
1	21	2	2	5	2	7	1	1	3	1	1	2
1	20	2	2	6	1	7	1	2	1	4	2	4
1	27	2	1	4	1	6	1	4	3	2	4	5
1	21	2	2	6	2	6	1	2	1	2	3	3
1	23	3	3	4	3	4	2	2	3	2	5	1
1	22	2	2	4	2	4	2	2	2	2	4	1
1	-	3	4	4	2	5	2	3	2	2	2	1
1	18	3	2	6	4	6	1	4	5	4	3	5
1	19	3	3	6	2	7	1	1	2	2	1	2
1	22	2	4	4	3	7	1	2	2	4	3	3
1	18	6	5	6	4	6	4	4	2	3	3	4
1	23	3	2	6	1	5	5	6	1	2	3	2
1	19	3	3	6	3	7	2	5	4	2	6	3
1	29	1	1	7	1	6	1	3	1	6	5	3
1	19	2	1	6	1	7	1	1	1	1	2	1
1	20	1	2	7	1	7	1	1	1	3	4	5
1	29	1	3	5	2	6	1	1	1	3	3	3
1	24	3	3	3	3	5	1	1	1	1	1	1
1	21	1	3	5	1	7	1	1	1	3	4	4
1	22	1	3	7	4	7	1	1	1	3	1	3
1	33	5	3	6	5	7	2	4	4	5	6	6
1	20	3	2	6	2	6	2	4	2	2	2	3
1	31	2	2	4	2	5	4	3	3	2	4	1
1	22	3	2	6	2	7	1	1	2	2	2	2
1	24	3	1	6	1	2	2	2	1	1	5	1
1	18	2	1	4	1	6	1	1	1	2	2	1
1	27	3	1	4	1	5	2	2	2	4	4	2
1	20	3	4	7	4	7	3	5	3	5	4	5
1	17	2	5	6	3	7	3	4	1	3	3	1
1	22	5	2	7	2	5	3	6	2	1	6	2
1	20	4	2	5	2	7	7	6	2	1	5	2
1	25	5	3	6	3	5	1	4	2	5	4	3
1	21	3	3	4	2	6	2	3	3	3	3	3
1	21	1	3	2	1	2	2	2	1	2	1	1
1	24	1	1	3	2	6	1	2	1	2	2	1
1	20	2	5	6	1	5	5	4	1	2	2	1
1	25	3	3	5	2	5	2	4	3	5	3	5
1	17	2	4	6	3	7	1	1	2	2	2	4
1	21	4	3	6	2	5	3	2	3	1	6	2
1	18	4	3	4	4	5	4	3	1	1	4	5
1	22	4	4	5	3	5	2	3	3	5	2	5
1	21	5	3	7	3	4	2	6	2	5	3	3
1	21	5	5	6	2	6	4	4	1	4	5	3
1	20	3	3	6	4	6	4	3	3	3	4	3
1	24	1	3	5	1	6	1	1	1	3	2	5
1	20	2	2	5	3	6	2	3	1	3	5	4
1	22	2	2	7	1	7	4	2	1	2	1	1
1	22	3	2	6	2	5	2	4	2	3	5	5
1	21	2	1	6	1	6	1	1	6	1	4	2
1	20	5	4	4	2	5	4	5	2	1	2	1
1	21	1	4	3	1	5	1	3	1	1	1	1
1	20	1	2	3	1	7	1	2	1	1	1	1
1	19	5	4	5	2	6	3	4	2	4	2	3
1	23	3	2	5	2	5	2	4	-	4	3	5
1	25	4	1	3	1	5	5	6	2	2	5	1
1	20	2	5	6	2	6	2	5	2	5	4	3
1	-	4	2	5	1	6	3	3	2	2	3	2
1	26	2	2	6	3	6	1	1	2	1	1	2
1	21	4	2	6	4	7	2	3	4	3	5	2
1	23	4	2	4	1	5	1	3	2	4	2	1
1	19	4	6	6	2	6	2	2	1	2	3	1
1	22	2	2	6	2	5	2	4	3	3	3	2
1	21	2	3	5	3	6	1	2	2	2	3	3
1	23	5	5	7	3	7	5	7	4	4	6	4
1	18	1	2	5	1	6	1	1	1	3	3	2
1	20	3	6	7	4	6	4	6	2	4	3	3
1	25	2	2	6	1	4	2	3	3	2	2	4
1	48	2	2	3	4	5	2	4	5	3	6	3

Table D.1 (*Continued*)

Version	Age	Romania	Puerto Rico	Russia	South Africa	Spain	Srilanka	Swaziland	Switzerland	Turkey	Ukraine	Venezuela	Wales
1	26	3	1	5	3	5	1	2	2	2	2	4	1
1	20	3	2	5	5	5	3	4	1	3	5	2	3
1	19	3	3	6	3	5	2	3	1	2	4	2	3
1	22	3	5	4	5	3	2	1	1	2	3	2	2
1	19	3	4	4	2	5	2	2	2	3	4	1	2
1	25	2	5	5	6	5	3	3	2	5	4	2	4
1	18	2	2	3	2	2	1	1	4	3	1	2	1
1	20	3	3	6	3	6	4	3	4	5	4	3	5
1	22	3	2	5	1	3	3	2	1	1	2	1	1
1	21	4	4	4	4	5	3	3	4	3	3	3	3
1	20	5	3	5	3	5	1	1	1	2	4	1	1
1	23	4	2	4	2	5	2	3	1	2	4	1	1
1	21	2	2	3	3	4	3	2	2	2	2	1	1
1	22	4	3	3	3	4	3	2	1	5	4	2	1
1	20	2	4	4	2	6	3	2	1	2	3	1	2
1	20	4	4	6	5	7	3	3	4	3	4	5	3
1	18	4	5	5	3	4	2	2	2	2	3	2	1
1	23	2	4	5	3	5	1	2	2	5	3	2	2
1	19	2	2	5	2	5	2	5	2	4	3	3	1
1	27	1	1	1	1	3	1	1	1	1	1	1	1
1	20	3	1	1	1	3	2	2	1	3	1	1	1
1	19	1	1	1	2	5	2	1	1	2	2	2	2
1	21	3	5	6	5	6	2	2	2	4	3	3	1
1	18	2	4	6	1	4	1	1	1	6	1	1	1
1	18	2	4	3	4	6	3	1	2	3	3	4	1
1	21	2	2	3	3	3	1	1	1	1	3	1	1
1	20	2	2	2	5	5	1	1	1	2	3	3	1
1	27	4	4	6	5	5	1	2	2	3	3	1	1
1	21	4	2	2	3	5	2	2	2	2	2	1	2
1	23	3	3	5	3	4	2	2	1	3	5	1	4
1	22	2	2	6	2	5	1	2	1	2	3	1	2
1	-	2	2	3	3	4	1	1	2	2	-	2	2
1	18	6	4	5	6	4	1	1	3	3	4	2	2
1	19	3	4	2	5	7	1	1	1	2	1	2	1
1	22	2	1	5	5	7	3	1	4	2	4	3	1
1	18	3	2	2	1	3	1	2	5	1	1	2	1
1	23	2	1	3	4	5	4	3	1	4	2	2	1
1	19	5	2	5	3	6	3	2	3	3	4	1	2
1	29	1	1	1	1	7	1	1	2	5	1	1	1
1	19	1	1	1	1	6	1	1	1	1	1	1	1
1	20	6	5	6	2	7	1	1	2	2	4	1	1
1	29	3	1	3	2	3	1	1	1	1	1	2	1
1	24	1	3	5	2	2	1	1	1	1	2	3	1
1	21	4	5	3	4	4	1	1	2	1	5	1	1
1	22	1	2	3	5	5	1	1	1	1	3	1	-
1	33	4	4	5	4	5	3	3	4	5	4	4	2
1	20	5	3	6	3	5	1	3	2	4	4	1	1
1	31	3	3	4	3	4	2	3	2	3	4	2	5
1	22	2	4	2	3	5	1	1	1	3	-	1	1
1	24	2	1	2	1	3	3	3	2	2	4	2	1
1	18	2	2	3	1	5	1	1	1	1	1	1	1
1	27	4	3	5	1	2	1	1	1	2	2	1	1
1	20	5	2	4	3	5	2	3	3	4	3	3	2
1	17	3	4	5	2	4	3	3	5	4	4	1	1
1	22	2	2	2	3	6	2	2	1	6	2	1	1
1	20	-	3	1	5	1	2	7	2	3	1	2	1
1	25	3	2	3	2	6	3	1	3	4	2	5	1
1	21	3	4	5	4	5	1	1	4	2	2	2	1
1	21	1	1	3	1	3	2	1	1	1	1	1	1
1	24	2	1	3	3	1	2	1	1	1	4	1	1
1	20	3	2	2	2	3	1	4	2	2	3	3	3
1	25	4	2	4	4	5	4	3	2	4	5	4	1
1	17	4	2	5	3	6	1	1	2	2	2	2	2
1	21	4	5	5	3	3	2	1	1	2	3	1	2
1	18	4	2	4	5	4	2	2	1	2	1	1	1
1	22	2	4	3	3	3	2	2	4	3	3	3	2
1	21	2	3	3	3	4	2	3	1	2	2	1	1
1	21	3	4	5	3	2	2	5	1	2	2	2	1
1	20	4	3	5	5	7	3	2	2	2	4	1	4
1	24	6	2	3	5	6	1	1	1	1	1	2	1
1	20	6	5	2	1	2	2	2	1	6	5	2	1
1	22	4	3	5	2	5	1	4	1	1	1	5	1
1	22	4	3	3	2	6	2	2	2	6	1	1	2
1	21	3	3	5	2	3	1	1	1	4	2	1	1
1	20	1	2	4	3	4	2	6	3	1	3	2	1
1	21	1	2	1	1	5	1	1	4	1	1	1	1
1	20	1	3	1	5	1	1	1	1	1	1	1	1
1	19	3	2	3	2	2	1	3	2	2	1	2	1
1	23	2	4	6	4	5	2	2	2	2	2	2	3
1	25	2	2	3	2	4	1	2	2	4	1	2	1
1	20	2	3	6	5	6	2	2	6	5	-	1	1
1	-	3	2	5	4	4	3	2	1	2	2	1	1
1	26	1	3	4	3	6	1	1	1	2	3	1	1
1	21	4	2	6	4	7	2	2	1	1	1	1	1
1	23	3	2	5	5	4	1	1	4	3	3	1	2
1	19	5	3	4	4	5	1	2	2	2	2	1	1
1	22	2	3	3	2	4	3	2	2	3	2	2	2
1	21	2	4	4	4	6	1	1	3	2	2	3	2
1	23	5	5	7	4	6	3	3	3	5	4	4	2
1	18	7	5	4	3	4	1	1	1	1	1	1	2
1	20	2	3	5	6	5	3	4	3	5	1	2	1
1	25	3	5	5	3	5	1	2	-	3	1	2	1
1	48	1	4	4	1	3	4	2	4	2	1	2	1

Table D.1 (*Continued)*

Version	Age	Bahamas	Argentinie	England	Australia	Bolivia	Brazil	Germany	Canada	China	Colombia	Denmark
2	20	3	4	3	4	4	4	4	3	3	3	4
2	22	2	4	3	4	2	3	1	1	1	3	4
2	26	1	3	1	2	1	4	1	1	1	1	1
2	19	4	5	2	5	3	6	2	4	3	4	6
2	19	4	6	3	6	1	6	3	3	2	3	5
2	21	3	5	2	4	2	5	1	1	1	5	5
2	21	4	3	1	3	1	4	1	1	1	1	3
2	20	5	4	2	3	4	6	2	1	1	3	3
2	24	7	7	3	5	1	7	1	2	1	1	5
2	19	6	6	3	6	3	6	2	2	1	4	5
2	21	5	6	4	5	4	3	3	2	1	2	3
2	22	7	6	4	6	3	4	2	2	1	4	6
2	18	4	4	3	4	2	5	1	2	2	3	3
2	19	4	6	3	7	5	6	2	2	2	5	5
2	16	1	3	1	4	-	5	2	1	1	1	2
2	20	5	5	1	1	1	7	1	1	1	2	6
2	21	1	2	2	5	3	5	3	2	1	1	2
2	17	2	7	2	4	4	6	1	2	1	3	5
2	21	5	5	5	5	3	5	4	5	3	5	5
2	21	4	5	2	2	1	5	1	1	1	1	5
2	18	4	5	2	6	2	6	1	1	1	4	5
2	21	4	4	2	-	1	7	1	1	1	4	2
2	25	4	4	3	4	1	5	4	3	2	4	5
2	25	4	4	3	5	3	4	3	2	3	3	4
2	24	2	3	2	3	2	4	2	2	2	2	3
2	20	4	3	4	5	1	4	1	1	1	5	2
2	20	3	7	4	5	3	6	2	2	1	3	4
2	18	1	6	3	6	3	6	1	1	1	1	3
2	24	4	6	1	6	1	5	1	1	1	2	5
2	23	7	4	2	3	3	4	4	2	5	6	7
2	22	2	5	2	5	4	5	3	1	2	3	4
2	20	2	5	5	4	2	5	2	2	1	4	5
2	28	1	1	1	2	1	2	1	1	1	1	1
2	20	4	5	3	3	2	6	1	1	2	4	3
2	21	1	6	2	4	2	7	1	1	1	2	3
2	26	4	3	3	4	2	5	2	3	4	3	3
2	38	6	5	3	4	2	6	1	2	1	2	4
2	21	5	4	3	3	1	1	1	1	1	1	1
2	18	5	6	1	5	2	5	2	1	1	4	5
2	18	3	3	2	2	1	5	1	1	1	3	4
2	22	3	1	1	2	1	2	1	1	1	1	1
2	22	3	4	3	5	2	3	4	1	2	5	6
2	21	2	1	3	6	2	3	1	4	3	1	5
2	20	4	5	4	5	3	5	1	1	1	5	6
2	22	3	4	3	5	3	5	2	2	4	3	4
2	20	4	6	1	7	1	6	1	1	1	1	3
2	26	4	4	1	1	1	3	3	1	1	1	1
2	24	3	4	3	7	3	6	3	4	3	4	7
2	27	3	4	6	5	4	5	4	4	4	5	6
2	22	5	4	3	5	3	4	2	2	2	4	3
2	25	6	5	3	6	2	6	3	2	2	5	4
2	22	5	2	2	4	1	3	2	2	1	1	4
2	23	2	4	3	5	5	5	3	3	2	2	-
2	20	6	7	5	6	4	5	1	3	4	3	6
2	20	1	5	1	1	3	4	1	1	1	-	1
2	19	4	5	5	6	5	5	3	-	2	5	5
2	23	4	4	2	2	1	4	1	1	3	1	4
2	19	7	7	2	5	4	5	1	2	1	2	5
2	20	5	5	3	3	2	6	2	2	2	2	5
2	17	4	6	1	7	4	6	2	2	2	1	5
2	19	5	5	5	3	2	5	2	1	1	3	6
2	24	1	2	1	5	1	1	1	2	2	1	1
2	21	2	4	5	4	1	4	1	1	1	1	5
2	22	3	4	4	6	3	6	2	3	5	6	5
2	23	2	4	2	4	1	3	1	2	1	2	5
2	22	4	6	2	5	1	6	2	2	1	5	3
2	21	5	2	1	1	3	5	3	1	1	2	1
2	30	6	3	1	2	2	2	3	2	3	4	5
2	20	5	3	4	5	3	4	3	3	2	4	4
2	18	5	4	2	1	3	5	3	2	1	3	4
2	20	6	5	2	4	2	4	2	2	3	2	3
2	19	5	4	4	6	3	5	2	2	-	3	4
2	27	2	2	1	3	2	4	1	1	3	4	3
2	22	6	4	4	4	2	6	2	1	1	4	3
2	23	6	7	3	7	2	6	1	2	2	2	4
2	18	4	2	3	4	3	5	2	2	2	3	2
2	18	4	6	4	3	1	7	1	1	1	2	6
2	17	3	4	2	4	2	4	1	2	3	2	3
2	19	5	3	5	6	5	6	3	-	2	3	5
2	22	4	6	3	6	2	6	2	1	1	1	1
2	20	5	6	5	7	3	7	1	4	2	2	7
2	19	5	6	4	3	4	7	1	5	2	3	4
2	17	6	6	2	7	2	6	1	1	1	6	5
2	20	3	5	4	-	3	7	3	3	3	2	4
2	22	6	6	5	4	2	7	1	1	1	1	7
2	18	5	7	1	3	1	5	2	1	1	1	6
2	19	3	5	6	5	4	5	3	2	2	3	7
2	20	4	6	5	5	3	5	3	2	1	6	3
2	20	4	2	2	5	1	6	1	1	1	3	6
2	20	4	5	3	6	4	4	3	3	1	4	2
2	25	2	6	3	6	2	5	2	4	3	5	3
2	22	4	4	5	6	3	7	2	2	2	4	6
2	21	5	5	3	5	5	3	3	3	2	4	5
2	26	3	4	5	5	3	4	1	1	3	4	3
2	19	5	6	4	6	4	6	6	4	3	3	6

Table D.1 (*Continued*)

Version	Age	France	Ghana	Guadaloupe	Ireland	Latvia	Japan	Italy	India	DominicanR	Korea	Curacao	Austria
2	20	3	3	3	4	4	2	5	2	2	2	3	4
2	22	3	1	1	1	2	1	5	1	1	1	1	6
2	26	1	5	1	1	1	1	5	1	1	1	1	2
2	19	3	5	2	2	2	1	4	1	1	1	4	4
2	19	3	1	1	3	2	1	6	1	1	1	3	6
2	21	1	1	1	1	2	1	1	1	1	1	1	5
2	21	2	1	1	2	1	1	3	1	1	1	1	5
2	20	1	2	2	2	2	1	4	1	1	1	1	1
2	24	5	4	3	4	1	1	6	1	1	1	4	2
2	19	3	4	2	4	2	3	-	1	1	1	2	7
2	21	5	3	1	1	-	1	7	1	1	1	1	4
2	22	5	4	2	4	3	1	6	1	1	1	3	5
2	18	2	1	1	3	2	1	5	2	1	1	1	5
2	19	2	2	2	2	5	2	4	1	2	1	1	6
2	16	1	1	1	2	2	1	3	1	1	1	1	4
2	20	2	1	1	5	1	1	7	1	-	1	1	6
2	21	2	1	1	2	1	1	5	1	1	1	1	2
2	17	2	1	1	4	2	1	3	1	1	1	1	5
2	21	3	4	4	3	4	2	4	2	2	2	2	5
2	21	6	2	1	1	1	1	7	1	1	1	1	6
2	18	6	2	1	2	2	1	6	1	1	1	3	4
2	21	2	5	3	5	1	1	5	1	1	1	4	4
2	25	5	2	2	2	2	1	5	1	1	1	1	5
2	25	3	3	2	4	4	1	5	2	1	2	4	4
2	24	4	1	1	1	2	1	3	2	1	1	1	4
2	20	3	4	1	1	3	1	2	1	1	1	2	2
2	20	4	1	1	5	3	1	4	1	1	1	2	6
2	18	1	1	1	3	3	1	4	1	1	1	1	3
2	24	4	1	1	4	4	1	6	1	1	1	1	2
2	23	5	5	3	3	5	3	6	1	1	3	5	4
2	22	4	1	1	6	3	1	5	1	1	1	2	6
2	20	3	2	1	2	1	1	7	1	1	1	2	5
2	28	2	1	1	1	1	1	5	1	1	1	4	5
2	20	3	2	1	1	3	1	2	1	1	1	2	3
2	21	6	1	1	3	1	1	7	1	1	1	1	4
2	26	4	4	2	2	2	1	6	1	1	2	3	3
2	38	5	4	2	2	2	1	4	1	1	1	2	5
2	21	1	5	1	1	1	1	3	1	1	1	1	3
2	18	4	2	1	4	2	1	6	1	1	1	1	5
2	18	3	1	1	1	1	1	3	1	1	1	1	2
2	22	1	3	1	1	1	1	1	1	1	1	1	1
2	22	4	2	2	5	5	1	7	2	2	1	1	6
2	21	3	3	1	1	1	3	7	1	1	3	4	7
2	20	3	4	2	4	2	2	4	2	1	2	4	4
2	22	5	2	1	2	4	2	5	1	1	2	5	6
2	20	2	2	1	1	1	1	5	3	1	1	1	5
2	26	4	3	2	2	2	1	1	1	1	1	1	2
2	24	5	3	2	4	5	1	3	2	1	2	2	5
2	27	6	6	4	5	4	4	5	3	3	3	3	5
2	22	3	4	2	1	1	1	5	1	2	1	2	4
2	25	3	5	3	3	4	2	5	1	1	2	3	5
2	22	1	1	1	2	1	1	2	1	1	1	3	1
2	23	2	2	2	2	2	1	2	1	1	1	1	3
2	20	4	5	3	4	5	2	5	3	1	2	5	5
2	20	1	1	1	5	4	1	6	1	1	1	1	4
2	19	3	2	2	6	5	2	5	1	1	1	2	5
2	23	4	1	1	3	1	1	7	1	1	-	-	2
2	19	2	4	1	1	2	1	3	1	1	1	1	4
2	20	4	5	3	3	2	2	2	1	1	1	5	5
2	17	2	-	1	5	2	1	7	1	1	1	6	3
2	19	2	1	1	2	6	1	2	2	1	1	1	6
2	24	1	1	1	3	1	1	1	-	1	1	1	1
2	21	3	2	1	2	1	1	2	1	2	1	2	2
2	22	3	5	2	4	3	3	3	4	2	2	5	5
2	23	2	2	1	1	2	2	5	1	1	1	1	1
2	22	4	4	1	5	1	1	3	1	1	1	1	5
2	21	2	5	1	1	1	1	6	1	1	1	5	5
2	30	3	3	3	4	2	1	6	1	1	1	5	6
2	20	3	4	4	4	4	2	6	2	2	2	2	5
2	18	3	5	3	1	1	1	5	1	1	1	2	4
2	20	2	4	2	2	2	2	4	2	2	2	2	2
2	19	3	4	-	3	2	1	2	1	1	-	2	2
2	27	4	3	2	1	1	1	3	1	1	1	3	2
2	22	3	1	1	4	2	1	2	1	1	1	4	2
2	23	3	5	3	2	3	2	4	2	1	2	2	5
2	18	2	4	2	4	3	1	5	2	1	1	2	5
2	18	2	1	1	4	1	1	4	1	1	1	1	5
2	17	3	2	2	2	1	1	5	1	1	2	2	3
2	19	5	5	1	5	4	1	6	3	1	1	2	6
2	22	1	5	2	2	2	1	3	1	1	1	1	4
2	20	6	5	2	6	2	1	5	1	1	1	6	7
2	19	4	2	2	5	1	1	1	1	1	1	1	5
2	17	4	3	3	1	-	1	6	3	1	1	3	4
2	20	5	2	-	5	3	2	2	1	1	2	2	6
2	22	1	2	1	7	1	1	4	1	1	1	1	3
2	18	1	4	1	1	1	1	7	1	1	1	2	1
2	19	4	1	1	2	4	2	4	2	2	1	4	6
2	20	2	3	1	3	4	1	6	1	1	1	4	4
2	20	4	1	1	3	3	1	4	1	1	1	1	5
2	20	2	2	1	3	3	1	7	1	1	1	4	4
2	25	7	3	2	3	2	2	4	1	1	1	4	5
2	22	4	2	1	4	4	2	4	1	1	1	1	5
2	21	4	1	1	4	4	1	4	1	1	1	4	4
2	26	2	5	2	3	2	1	1	1	1	1	1	1
2	19	5	4	4	6	4	4	6	3	3	3	4	5
2	22	3	4	3	2	2	2	3	2	2	2	5	4
2	19	3	3	3	3	2	2	6	1	2	1	3	4
2	20	5	3	1	1	4	1	4	1	1	1	2	6
2	20	2	-	1	2	3	1	6	1	2	1	2	5
2	20	2	4	3	4	3	1	3	3	1	3	4	4
2	23	5	6	2	6	3	1	5	1	1	1	5	3
2	20	1	4	1	3	2	1	6	1	1	1	2	6

Table D.2: Attractiveness ratings of Mister World 2014 (dynamic thin slices)

Version	Age	Bahamas	Argentina	England	Australia	Bolivia	Brazil	Germany	Canada	China	Colombia	Denmark
1	26	6	5	4	5	2	5	5	4	3	4	5
1	20	5	5	4	6	3	5	2	3	3	4	5
1	19	4	3	5	7	4	5	3	2	4	5	6
1	22	3	2	3	7	3	5	2	1	2	2	6
1	19	4	4	5	7	2	6	5	2	2	4	3
1	25	4	5	5	6	4	6	3	5	5	3	6
1	18	1	6	5	6	2	6	4	2	2	3	6
1	20	5	5	4	5	5	5	5	4	5	6	6
1	22	4	4	3	5	1	3	1	3	1	3	4
1	21	6	7	4	5	4	6	4	4	3	4	4
1	20	5	7	3	5	2	6	2	1	1	4	2
1	23	4	4	3	5	3	6	2	2	2	4	5
1	21	5	7	4	5	4	5	2	3	3	4	4
1	22	6	4	3	5	3	4	2	2	4	5	5
1	20	3	6	2	5	4	5	2	1	2	3	5
1	20	4	6	6	6	4	7	3	3	3	6	4
1	18	3	5	5	6	2	5	2	2	1	3	5
1	23	4	2	2	5	2	5	4	3	2	4	6
1	19	6	5	4	5	3	2	1	2	1	2	1
1	27	3	4	4	1	1	1	1	1	1	1	1
1	20	2	4	2	5	1	4	1	1	2	2	6
1	19	5	6	5	7	4	3	2	2	1	7	5
1	21	3	5	3	6	2	5	2	2	2	4	3
1	18	2	5	1	5	1	5	1	1	2	3	5
1	18	4	4	4	5	5	6	3	2	5	5	5
1	21	5	7	4	5	2	7	2	3	2	-	-
1	20	5	6	5	4	2	5	1	3	1	3	2
1	27	2	5	5	7	1	6	1	3	3	3	5
1	21	3	4	4	5	4	6	2	2	1	2	6
1	23	3	5	3	5	2	5	3	3	4	3	4
1	22	3	6	2	2	4	4	1	2	2	2	6
1	-	3	4	4	5	3	4	4	5	2	2	5
1	18	5	6	5	5	4	7	3	2	2	4	6
1	19	2	7	6	5	3	6	2	2	1	2	2
1	22	3	6	6	4	5	3	2	4	3	2	6
1	18	5	5	2	4	2	5	1	1	1	1	1
1	23	5	6	3	6	2	5	2	2	3	4	4
1	19	3	5	4	5	3	5	2	2	2	4	5
1	29	2	3	1	4	1	1	4	2	1	1	3
1	19	3	6	2	4	1	5	1	1	1	1	2
1	20	3	6	7	6	1	3	1	1	1	4	7
1	29	3	3	3	3	1	6	5	1	1	4	5
1	24	1	4	5	5	3	5	1	1	1	1	4
1	21	2	6	5	7	5	7	2	1	1	3	6
1	22	1	6	7	7	1	7	1	2	1	1	6
1	33	6	5	5	6	4	5	5	5	5	5	6
1	20	4	4	5	5	3	6	3	2	3	5	6
1	31	4	3	4	6	3	5	1	2	2	5	6
1	22	2	6	2	5	2	5	1	2	2	3	5
1	24	3	5	1	1	2	1	1	2	1	3	3
1	18	1	6	3	6	1	4	1	1	1	1	2
1	27	2	4	3	5	2	5	2	1	2	2	3
1	20	4	5	3	4	2	5	3	3	3	3	6
1	17	-	6	6	6	-	6	3	-	1	1	3
1	22	3	6	2	5	1	6	1	2	2	2	5
1	20	2	4	2	5	1	6	6	3	1	4	5
1	25	5	5	3	5	4	5	1	4	2	5	2
1	21	4	5	5	6	5	6	3	2	2	4	5
1	21	2	4	1	4	3	6	1	2	2	4	4
1	24	2	4	2	5	1	6	1	1	1	1	7
1	20	5	5	5	7	4	7	2	2	2	4	5
1	25	5	6	5	6	2	6	3	5	2	4	5
1	17	3	5	6	4	5	5	2	3	3	2	3
1	21	4	5	3	5	3	5	3	2	4	2	6
1	18	2	6	2	4	2	5	5	3	1	2	5
1	22	2	6	3	5	3	3	4	3	2	4	6
1	21	3	5	5	5	4	6	5	4	3	5	6
1	21	4	6	4	5	3	6	1	5	2	1	4
1	20	4	4	4	6	3	6	3	3	2	5	4
1	24	5	7	6	7	4	6	1	1	1	5	7
1	20	2	3	4	6	4	5	3	1	3	4	5
1	22	6	5	4	7	1	6	1	1	1	4	3
1	22	4	6	4	5	3	5	1	1	1	4	5
1	21	3	4	4	7	2	4	2	1	4	2	2
1	20	5	5	2	4	1	5	-	3	-	3	2
1	21	4	2	2	4	1	6	1	1	1	-	2
1	20	6	4	3	3	1	4	1	1	1	2	5
1	19	4	3	4	4	2	5	2	1	1	3	2
1	23	4	6	4	6	2	6	3	2	2	4	6
1	25	6	7	4	5	2	5	1	4	1	2	2
1	20	6	6	6	7	2	7	2	2	1	5	6
1	-	2	3	2	3	2	5	3	4	2	2	5
1	26	2	4	2	5	2	6	1	1	3	5	3
1	21	4	4	3	5	1	6	1	2	3	2	5
1	23	4	4	2	6	5	6	4	2	1	3	5
1	19	2	6	4	6	2	5	2	2	1	2	6
1	22	4	2	4	6	3	4	3	2	2	4	5
1	21	4	6	5	6	3	5	3	2	2	3	6
1	23	6	6	3	6	2	7	4	4	3	4	7
1	18	3	7	6	7	2	6	2	1	1	5	6
1	20	5	5	3	7	3	5	2	4	4	2	3
1	25	2	4	3	7	2	2	1	1	2	2	4
1	48	7	4	4	4	3	4	3	3	4	4	5

Table D.2 (*Continued*)

Version	Age	France	Ghana	Guadaloupe	Ireland	Latvia	Japan	Italy	India	DominicanR	Korea	Curacao	Austria
1	26	4	4	2	4	2	1	3	1	2	1	4	4
1	20	5	5	2	2	3	2	3	2	1	2	3	5
1	19	5	2	3	2	2	1	4	1	2	2	2	5
1	22	1	2	2	1	3	1	5	2	3	2	3	5
1	19	5	5	2	1	3	2	5	2	1	2	3	5
1	25	6	3	3	5	5	2	5	2	1	2	5	6
1	18	3	1	2	5	2	1	4	1	2	2	2	5
1	20	4	4	3	5	3	3	5	3	3	3	3	4
1	22	3	6	3	1	2	1	3	1	1	2	3	5
1	21	4	5	3	4	4	2	6	2	3	2	2	5
1	20	3	1	1	2	3	1	2	1	1	1	1	3
1	23	5	4	4	1	2	1	6	1	1	1	2	4
1	21	4	4	3	2	3	3	3	3	1	3	3	4
1	22	4	5	3	3	2	2	5	1	1	2	3	4
1	20	6	3	1	4	4	1	5	3	1	2	1	4
1	20	6	4	4	4	2	4	6	4	2	3	3	5
1	18	1	1	1	3	3	1	3	1	1	1	1	3
1	23	4	5	3	5	2	3	5	3	2	2	2	-
1	19	2	6	2	5	1	1	4	2	1	1	2	1
1	27	1	1	1	1	1	1	1	1	1	1	1	1
1	20	4	3	1	3	1	1	3	1	1	1	3	2
1	19	5	2	1	7	6	2	7	3	1	1	2	5
1	21	3	3	3	5	4	1	6	2	2	1	2	6
1	18	3	2	1	3	1	1	1	1	1	1	2	6
1	18	4	2	1	3	5	1	5	2	1	1	3	6
1	21	2	1	1	3	2	1	-	1	1	2	1	3
1	20	2	1	1	2	2	1	-	1	1	1	2	5
1	27	6	-	1	1	3	1	-	1	1	1	1	5
1	21	3	2	2	4	2	1	5	2	1	1	2	5
1	23	3	5	2	2	3	1	4	1	1	3	2	3
1	22	4	4	2	3	1	2	3	2	1	1	1	5
1	-	5	2	2	2	4	2	3	1	1	2	1	6
1	18	5	1	1	5	3	1	6	1	3	2	2	6
1	19	5	1	1	5	3	1	3	1	2	1	1	7
1	22	3	1	1	5	4	2	6	1	2	2	3	4
1	18	3	5	1	2	1	1	7	4	2	1	2	3
1	23	3	6	5	3	2	1	5	2	2	1	6	3
1	19	5	2	2	6	2	1	5	2	2	1	2	5
1	29	2	1	1	3	1	1	7	5	1	1	4	1
1	19	2	1	1	1	1	1	6	1	1	1	1	6
1	20	5	1	1	6	4	1	6	1	1	1	1	6
1	29	1	1	1	1	1	1	5	1	1	1	1	1
1	24	2	1	1	1	1	1	1	1	-	1	1	1
1	21	1	1	1	3	5	1	3	1	1	1	2	6
1	22	2	1	1	4	3	1	4	1	1	1	1	4
1	33	6	6	3	5	5	2	6	3	2	3	4	5
1	20	6	2	2	4	3	2	6	4	1	2	5	6
1	31	4	4	3	2	2	2	2	1	1	1	2	3
1	22	3	1	1	1	1	1	4	1	1	1	1	4
1	24	2	5	1	1	2	1	1	1	1	1	1	2
1	18	3	4	1	1	2	1	4	1	1	1	1	5
1	27	4	2	2	2	2	2	3	1	1	1	2	3
1	20	5	4	3	3	2	1	6	1	1	2	2	5
1	17	1	3	3	5	1	2	5	1	1	2	3	3
1	22	4	5	2	3	1	1	6	2	1	2	3	5
1	20	4	7	4	4	2	1	5	4	1	1	3	7
1	25	4	1	1	5	2	1	6	2	5	1	3	3
1	21	4	2	1	4	2	1	3	1	1	1	2	3
1	21	2	2	2	2	1	1	3	1	1	1	1	2
1	24	2	1	1	1	1	1	2	1	1	1	1	2
1	20	5	7	3	2	1	-	2	1	1	1	2	2
1	25	4	5	3	4	2	1	5	1	1	1	2	5
1	17	4	1	2	5	4	2	5	2	1	2	1	5
1	21	5	3	1	3	4	2	2	1	1	1	1	3
1	18	5	5	6	4	3	3	1	1	1	2	3	5
1	22	2	2	2	3	2	2	6	3	2	1	2	3
1	21	3	5	2	3	1	1	5	2	1	1	2	5
1	21	2	3	3	5	2	2	-	1	5	2	1	5
1	20	5	2	1	6	5	1	4	2	2	2	1	5
1	24	5	1	-	5	1	1	6	1	1	1	1	6
1	20	6	3	2	5	3	1	7	1	1	1	1	2
1	22	1	5	4	7	1	1	2	1	1	1	6	6
1	22	4	4	2	3	1	1	7	3	2	2	2	5
1	21	4	1	1	3	2	2	2	2	2	2	1	3
1	20	4	5	4	3	4	1	2	4	1	1	2	3
1	21	1	1	1	1	1	1	1	1	1	1	1	4
1	20	3	1	1	5	4	1	5	1	1	1	2	5
1	19	2	4	1	4	2	1	4	1	1	1	3	4
1	23	3	5	2	4	3	2	5	2	2	2	2	5
1	25	1	5	3	4	2	1	3	2	1	1	1	2
1	20	3	2	2	5	2	1	2	2	1	1	1	5
1	-	3	6	2	2	2	2	4	2	2	3	2	5
1	26	6	1	1	5	2	3	5	1	1	1	1	5
1	21	6	5	3	1	3	2	4	1	2	2	3	6
1	23	5	3	1	4	3	1	4	1	2	1	1	4
1	19	5	5	1	3	5	1	6	1	1	1	1	4
1	22	2	3	2	2	3	3	3	2	2	3	5	4
1	21	3	1	1	4	2	2	6	1	1	1	3	6
1	23	-	7	5	6	3	2	5	3	4	-	5	6
1	18	4	1	1	4	2	1	4	2	1	1	1	4
1	20	5	6	3	7	1	3	6	4	1	3	5	5
1	25	4	1	1	6	2	1	4	1	1	1	1	4
1	48	2	4	2	2	2	2	6	3	1	2	3	2

Table D.2 (*Continued*)

Version	Age	Lebanon	Malta	Mexico	Moldova	Netherlands	Nigeria	Nireland	Paraguay	Peru	Philipines	Poland
2	20	3	4	5	4	5	2	3	4	4	5	6
2	22	3	6	7	3	7	1	5	3	2	4	4
2	26	5	3	6	1	6	1	3	1	3	4	1
2	19	3	6	7	2	7	2	2	4	1	1	3
2	19	3	6	6	4	7	1	2	2	5	5	5
2	21	1	2	6	1	6	1	1	1	2	2	2
2	21	2	1	5	1	5	1	1	4	2	2	2
2	20	2	2	6	3	6	2	2	1	3	1	1
2	24	5	3	5	2	7	2	6	4	5	3	1
2	19	5	3	6	1	7	1	3	1	5	4	3
2	21	2	4	7	1	7	1	-	5	4	2	2
2	22	2	5	6	3	7	2	5	2	4	5	2
2	18	2	3	6	2	6	1	1	2	4	3	2
2	19	2	3	5	4	7	2	2	5	4	6	4
2	16	2	2	5	4	6	1	1	2	2	1	3
2	20	3	3	6	3	7	1	1	2	7	4	5
2	21	2	3	6	4	6	1	3	1	5	6	6
2	17	4	5	6	4	7	2	2	2	5	3	2
2	21	4	5	6	4	7	3	5	3	4	5	3
2	21	6	-	7	3	6	1	1	2	4	4	1
2	18	4	5	7	2	6	1	5	5	5	2	5
2	21	3	3	6	4	4	5	5	3	5	5	1
2	25	4	5	5	3	7	2	4	2	4	3	3
2	25	3	2	6	4	5	5	4	3	5	5	3
2	24	3	2	6	4	2	1	1	2	3	4	3
2	20	1	4	7	2	3	1	4	1	2	6	1
2	20	2	3	6	3	7	1	1	4	5	4	3
2	18	3	4	3	4	6	1	1	1	2	1	3
2	24	2	2	6	1	7	1	1	2	5	4	3
2	23	3	4	6	3	6	3	6	6	3	5	4
2	22	3	4	6	3	7	1	3	4	5	4	3
2	20	3	4	6	1	6	1	5	1	4	3	3
2	28	4	2	5	1	4	1	3	1	2	4	3
2	20	4	3	4	2	6	1	2	3	2	3	2
2	21	2	1	7	1	7	1	1	1	1	1	5
2	26	3	2	6	2	4	2	5	4	2	5	3
2	38	6	4	6	2	6	4	3	2	3	4	2
2	21	1	2	7	1	7	1	5	1	4	3	2
2	18	3	2	7	2	7	1	3	2	3	2	2
2	18	4	2	6	2	5	2	2	2	2	2	2
2	22	3	1	6	5	4	2	1	1	1	1	1
2	22	4	5	7	3	7	1	3	5	6	4	2
2	21	2	4	2	1	4	2	2	2	3	3	1
2	20	3	2	6	1	6	2	2	4	2	5	3
2	22	3	4	6	3	6	1	2	2	5	5	3
2	20	2	4	6	1	7	1	3	2	6	5	6
2	26	5	2	6	1	4	2	4	1	1	1	1
2	24	3	3	6	1	7	2	3	2	2	4	2
2	27	2	4	6	2	6	3	4	5	4	5	5
2	22	3	3	6	3	5	3	3	4	5	4	2
2	25	5	5	7	5	6	4	5	3	5	5	3
2	22	5	7	5	4	6	1	1	1	7	5	1
2	23	4	3	4	2	4	2	4	4	-	4	4
2	20	5	5	7	5	7	3	4	4	3	5	2
2	20	2	4	5	6	7	1	1	2	6	4	4
2	19	5	6	6	4	6	2	5	4	5	4	5
2	23	2	5	6	2	3	1	1	2	3	3	4
2	19	4	2	7	3	7	5	5	1	2	5	1
2	20	3	3	5	2	6	2	5	4	3	5	4
2	17	2	5	5	3	6	1	3	1	3	4	5
2	19	3	4	7	3	7	1	1	3	5	6	3
2	24	4	3	4	1	2	1	3	2	1	1	5
2	21	4	5	7	3	7	2	5	3	4	3	5
2	22	5	3	6	3	6	4	4	3	4	6	2
2	23	3	7	7	2	6	1	3	2	4	4	5
2	22	2	3	5	1	6	1	4	3	4	4	5
2	21	5	7	6	2	6	5	5	1	6	3	3
2	30	2	3	6	5	4	1	3	2	5	4	3
2	20	5	4	6	3	5	2	4	4	3	4	4
2	18	6	5	6	3	6	3	2	3	2	5	5
2	20	5	4	7	-	5	4	4	-	4	5	3
2	19	3	5	7	2	6	3	5	2	5	4	3
2	27	3	2	4	1	6	4	1	3	1	6	3
2	22	4	5	4	3	5	1	2	1	5	4	3
2	23	6	3	6	2	7	2	4	2	3	5	3
2	18	2	3	5	2	6	2	3	5	4	4	2
2	18	5	1	7	2	6	1	2	1	5	1	2
2	17	3	4	6	2	6	2	4	2	3	5	3
2	19	3	3	5	3	6	1	5	3	6	2	2
2	22	5	2	7	1	7	1	6	3	4	5	2
2	20	2	6	4	2	7	2	6	3	3	6	1
2	19	4	2	6	3	7	2	1	1	5	3	6
2	17	4	5	6	4	7	2	4	3	5	7	2
2	20	3	5	6	2	3	1	3	3	2	6	3
2	22	2	3	6	2	5	1	2	1	5	3	5
2	18	1	4	6	1	5	1	2	1	2	4	7
2	19	2	4	6	3	5	1	-	-	5	4	3
2	20	2	3	6	4	6	1	2	2	4	4	4
2	20	2	3	5	3	6	1	2	1	3	2	3
2	20	3	2	7	3	6	1	4	5	4	5	3
2	25	5	3	7	2	4	4	5	3	1	6	2
2	22	2	3	4	1	5	1	2	2	4	1	4
2	21	4	5	7	1	7	1	2	3	4	5	4
2	26	4	1	6	2	6	1	5	4	1	5	3
2	19	4	5	6	4	7	1	4	3	4	3	5
2	22	5	2	7	5	6	2	5	4	2	2	4
2	19	2	5	6	4	6	5	5	3	3	4	4
2	20	1	2	5	3	6	3	4	2	5	3	2
2	20	3	4	6	1	5	1	3	1	4	5	4
2	20	4	3	5	3	4	4	5	2	4	5	4
2	23	3	4	7	2	6	2	5	2	3	4	4
2	20	4	4	7	2	6	1	2	1	3	3	2

Table D.2 (*Continued*)

Version	Age	Romania	Puertorico	Russia	South Africa	Spain	Srilanka	Swaziland	Switzerland	Turkey	Ukraine	Venezuela	Wales
2	20	4	4	5	5	4	3	2	3	3	4	2	3
2	22	2	4	4	4	4	3	1	1	1	1	2	1
2	26	1	1	2	3	4	1	1	1	1	1	1	1
2	19	1	5	6	4	5	2	1	1	3	2	1	2
2	19	4	5	5	5	6	4	1	4	3	2	3	2
2	21	1	2	5	2	5	1	1	1	1	2	1	2
2	21	3	1	3	1	5	1	1	1	1	1	1	1
2	20	1	1	5	2	5	2	1	1	1	1	1	1
2	24	1	5	6	5	7	1	2	3	4	4	2	1
2	19	2	2	7	2	6	1	2	1	5	2	3	2
2	21	2	4	5	4	6	1	1	1	5	2	1	2
2	22	3	3	5	4	5	2	2	3	3	2	2	3
2	18	2	4	5	4	6	2	1	2	2	4	2	3
2	19	5	3	6	7	7	3	2	3	4	5	2	3
2	16	2	3	2	2	3	2	1	2	1	1	1	1
2	20	2	3	6	6	7	1	2	7	7	1	1	1
2	21	4	2	3	1	4	1	1	1	1	1	1	2
2	17	2	3	4	3	2	1	1	1	1	4	2	1
2	21	3	3	4	5	5	4	3	2	2	2	3	3
2	21	1	1	4	2	6	1	1	1	2	1	1	1
2	18	1	4	5	3	7	1	1	2	4	2	3	1
2	21	1	4	6	2	6	1	3	1	1	4	1	4
2	25	3	2	4	3	6	2	2	2	4	2	2	-
2	25	1	4	5	5	5	3	2	2	1	3	-	3
2	24	3	2	4	4	6	4	1	1	2	2	3	2
2	20	1	1	6	1	5	1	1	3	1	5	1	1
2	20	2	6	6	3	7	2	1	1	5	2	4	-
2	18	5	-	6	5	3	2	1	1	2	4	1	-
2	24	1	1	6	3	4	1	1	1	2	1	1	1
2	23	2	2	5	3	6	4	5	3	6	2	2	2
2	22	4	5	4	4	7	2	1	-	6	4	3	2
2	20	2	2	5	5	6	2	1	1	1	2	3	2
2	28	1	1	3	1	2	1	1	1	1	1	1	1
2	20	3	2	6	3	4	2	2	1	3	3	3	1
2	21	1	4	6	5	4	1	1	1	1	3	1	1
2	26	4	4	6	1	5	2	2	1	2	2	1	3
2	38	2	2	4	5	4	2	3	2	3	2	2	2
2	21	1	2	5	1	4	3	1	1	1	1	1	1
2	18	2	2	6	5	6	1	1	2	4	3	2	2
2	18	3	3	3	2	5	2	2	2	2	2	2	2
2	22	1	1	1	1	1	1	1	1	1	1	1	1
2	22	2	2	4	2	7	2	1	2	1	3	2	2
2	21	1	1	2	5	5	2	1	1	1	1	1	2
2	20	5	5	5	4	3	3	3	2	2	3	1	2
2	22	2	4	7	4	7	3	1	1	4	2	2	2
2	20	1	4	5	1	1	1	1	1	2	1	1	1
2	26	1	1	1	1	3	2	4	1	4	2	2	1
2	24	2	2	6	3	4	2	2	2	3	5	2	3
2	27	6	5	5	4	5	5	3	4	5	5	3	3
2	22	3	4	5	3	3	4	3	2	3	4	2	5
2	25	4	4	6	5	6	5	4	2	3	4	1	1
2	22	2	2	1	4	6	1	1	1	1	1	2	1
2	23	3	3	4	4	3	3	2	2	1	2	2	2
2	20	3	4	6	3	7	2	4	1	5	4	3	3
2	20	3	6	6	5	6	3	1	1	3	-	-	1
2	19	4	3	5	5	4	2	2	3	4	3	2	4
2	23	3	2	6	-	2	2	1	2	1	2	2	2
2	19	2	4	7	5	4	2	2	2	1	5	1	1
2	20	4	3	6	4	5	3	2	3	4	5	3	3
2	17	3	6	5	5	7	1	1	1	6	3	1	1
2	19	2	4	6	4	6	1	1	2	1	1	1	1
2	24	2	2	2	2	2	5	1	1	1	1	1	1
2	21	1	1	1	3	4	5	1	1	1	1	1	1
2	22	3	4	6	3	5	3	2	1	2	5	3	3
2	23	1	2	5	2	6	3	1	2	2	1	3	1
2	22	5	2	6	2	4	2	1	1	4	2	1	1
2	21	2	1	2	1	4	1	2	5	3	1	2	1
2	30	4	1	4	4	6	3	2	2	1	1	5	1
2	20	4	3	4	3	5	3	4	1	3	3	2	1
2	18	3	1	4	2	4	4	3	1	3	3	3	1
2	20	3	2	4	2	3	2	2	3	2	2	3	2
2	19	3	2	4	2	5	1	3	3	1	4	2	5
2	27	1	1	3	1	5	5	2	2	3	1	1	1
2	22	2	1	4	2	5	2	1	4	1	2	1	1
2	23	2	4	4	4	5	2	1	1	3	2	2	1
2	18	2	2	6	2	3	2	4	2	2	3	2	2
2	18	4	1	6	1	4	1	1	1	1	2	1	1
2	17	3	4	5	4	3	2	2	3	3	2	3	2
2	19	2	5	5	6	7	2	2	1	5	2	4	3
2	22	1	1	6	2	6	4	1	1	3	1	1	2
2	20	4	1	5	5	7	5	1	3	6	4	1	2
2	19	2	3	5	4	2	1	2	1	1	2	1	1
2	17	2	2	4	6	5	4	3	1	3	4	1	1
2	20	2	4	5	4	3	2	-	2	2	6	1	1
2	22	4	3	3	5	4	1	2	1	1	3	1	1
2	18	2	2	5	2	4	1	1	3	2	1	2	1
2	19	3	5	6	4	5	2	1	4	3	3	3	4
2	20	2	4	6	4	5	3	2	2	3	5	3	4
2	20	2	3	3	5	6	2	1	1	3	1	1	1
2	20	1	4	4	1	6	1	1	2	-	1	1	1
2	25	3	5	7	2	5	2	3	2	-	2	1	2
2	22	3	3	2	4	4	3	1	2	1	2	1	2
2	21	2	2	5	6	4	3	1	5	3	2	4	2
2	26	1	4	3	4	5	4	3	1	2	1	2	3
2	19	6	6	7	6	6	6	2	2	3	3	4	3
2	22	2	3	4	3	4	3	4	2	2	3	2	3
2	19	5	3	5	5	5	3	3	5	3	3	3	2
2	20	1	4	6	2	5	1	5	1	1	2	2	1
2	20	4	4	5	5	6	2	2	1	1	2	1	1
2	20	3	4	4	3	4	3	3	4	5	4	2	2
2	23	3	3	5	4	6	3	3	3	2	4	4	1
2	20	2	4	3	3	5	1	3	1	1	2	1	1

E URLS OF THE MISTER WORLD 2014 PROFILE VIDEOS

Appendix E provides the links to the profile videos of the Mister World 2014 contests. The thin slices used in the study were extracted from these videos.

Table E.1: URLs of the Mister World 2014 profile videos

No	Country	Youtube URLs
1	Argentina	https://www.youtube.com/watch?v=7Frs-osKxKM&list=PLA7-iYleFX4zkh2iMpJmgC54EgDfGvxug&index=1
2	Australia	https://www.youtube.com/watch?v=S7JnUJB-Z9Y&list=PLA7-iYleFX4zkh2iMpJmgC54EgDfGvxug&index=2
3	Bahamas	https://www.youtube.com/watch?v=2k14B4W7gFI&list=PLA7-iYleFX4zkh2iMpJmgC54EgDfGvxug&index=4
4	Bolivia	https://www.youtube.com/watch?v=4vslRtEGFz4&list=PLA7-iYleFX4zkh2iMpJmgC54EgDfGvxug&index=5
5	Brazil	https://www.youtube.com/watch?v=I8cUwi2dUjo&index=6&list=PLA7-iYleFX4zkh2iMpJmgC54EgDfGvxug
6	Canada	https://www.youtube.com/watch?v=OWiYkqSqhJ8&index=7&list=PLA7-iYleFX4zkh2iMpJmgC54EgDfGvxug
7	China PR	https://www.youtube.com/watch?v=L9eNjrXQD7A&list=PLA7-iYleFX4zkh2iMpJmgC54EgDfGvxug&index=8
8	Colombia	https://www.youtube.com/watch?v=Xnvpnx8Fois&index=9&list=PLA7-iYleFX4zkh2iMpJmgC54EgDfGvxug
9	Curacao	https://www.youtube.com/watch?v=ITxdrRJeqqA&list=PLA7-iYleFX4zkh2iMpJmgC54EgDfGvxug&index=10
10	Denmark	https://www.youtube.com/watch?v=IxJVWCo7EuI&list=PLA7-iYleFX4zkh2iMpJmgC54EgDfGvxug&index=11
11	Dominican Republic	https://www.youtube.com/watch?v=DnxVdw7rFuQ&list=PLA7-iYleFX4zkh2iMpJmgC54EgDfGvxug&index=12
12	England	https://www.youtube.com/watch?v=V2kYADKuH34&list=PLA7-iYleFX4zkh2iMpJmgC54EgDfGvxug&index=13
13	France	https://www.youtube.com/watch?v=jiDuoj34Tu8&index=14&list=PLA7-iYleFX4zkh2iMpJmgC54EgDfGvxug
14	Germany	https://www.youtube.com/watch?v=1XoG4qcYgvw&index=15&list=PLA7-iYleFX4zkh2iMpJmgC54EgDfGvxug
15	Ghana	https://www.youtube.com/watch?v=zoFLKQpZB_M&index=16&list=PLA7-iYleFX4zkh2iMpJmgC54EgDfGvxug
16	Guadelope	https://www.youtube.com/watch?v=DLkM-Z-TE20&index=17&list=PLA7-iYleFX4zkh2iMpJmgC54EgDfGvxug
17	India	https://www.youtube.com/watch?v=5sgoI2_DR-M&list=PLA7-iYleFX4zkh2iMpJmgC54EgDfGvxug&index=18
18	Ireland	https://www.youtube.com/watch?v=3VMu9a4r9PQ&list=PLA7-iYleFX4zkh2iMpJmgC54EgDfGvxug&index=19
19	Italy	https://www.youtube.com/watch?v=MYWazwGb3b4&list=PLA7-iYleFX4zkh2iMpJmgC54EgDfGvxug&index=20
20	Japan	https://www.youtube.com/watch?v=vhiV-tIUTvo&list=PLA7-iYleFX4zkh2iMpJmgC54EgDfGvxug&index=21
21	Korea	https://www.youtube.com/watch?v=he6lU_sHnpg&index=22&list=PLA7-iYleFX4zkh2iMpJmgC54EgDfGvxug
22	Latvia	https://www.youtube.com/watch?v=CvHa_zZWGNg&list=PLA7-iYleFX4zkh2iMpJmgC54EgDfGvxug&index=23
23	Lebanon	https://www.youtube.com/watch?v=8ubFHlSsn-A&list=PLA7-iYleFX4zkh2iMpJmgC54EgDfGvxug&index=24
24	Malta	https://www.youtube.com/watch?v=P1evkXc9Kpg&list=PLA7-iYleFX4zkh2iMpJmgC54EgDfGvxug&index=25
25	Mexico	https://www.youtube.com/watch?v=naOgzf4OP3o&list=PLA7-iYleFX4zkh2iMpJmgC54EgDfGvxug&index=26
26	Moldova	https://www.youtube.com/watch?v=AwEAEp2dXQI&list=PLA7-iYleFX4zkh2iMpJmgC54EgDfGvxug&index=27
27	Netherlands	https://www.youtube.com/watch?v=YnVDGsWZ3VE&index=28&list=PLA7-iYleFX4zkh2iMpJmgC54EgDfGvxug
28	Nigeria	https://www.youtube.com/watch?v=IZXn4rlzCAo&list=PLA7-iYleFX4zkh2iMpJmgC54EgDfGvxug&index=29
29	Northern Ireland	https://www.youtube.com/watch?v=5SiK8O-qV4g&index=30&list=PLA7-iYleFX4zkh2iMpJmgC54EgDfGvxug
30	Paraguay	https://www.youtube.com/watch?v=gYPXT3AdnRc&index=31&list=PLA7-iYleFX4zkh2iMpJmgC54EgDfGvxug
31	Peru	https://www.youtube.com/watch?v=crjsRfMPfEY&index=32&list=PLA7-iYleFX4zkh2iMpJmgC54EgDfGvxug
32	Phillippines	https://www.youtube.com/watch?v=hoOtg-1Xh4o&index=33&list=PLA7-iYleFX4zkh2iMpJmgC54EgDfGvxug
33	Poland	https://www.youtube.com/watch?v=vEyom14_FiA&index=34&list=PLA7-iYleFX4zkh2iMpJmgC54EgDfGvxug
34	Puerto Rico	https://www.youtube.com/watch?v=9jqYioerc-Y&list=PLA7-iYleFX4zkh2iMpJmgC54EgDfGvxug&index=35
35	Romania	https://www.youtube.com/watch?v=PVOUCFsi49k&list=PLA7-iYleFX4zkh2iMpJmgC54EgDfGvxug&index=36
36	Russia	https://www.youtube.com/watch?v=sfWVIuY177w&list=PLA7-iYleFX4zkh2iMpJmgC54EgDfGvxug&index=37
37	South Africa	https://www.youtube.com/watch?v=T_jkGuX5C1o&list=PLA7-iYleFX4zkh2iMpJmgC54EgDfGvxug&index=38
38	Spain	https://www.youtube.com/watch?v=m6CMIUYqHls&list=PLA7-iYleFX4zkh2iMpJmgC54EgDfGvxug&index=39
39	Sri Langka	https://www.youtube.com/watch?v=fqc7vlBjHDA&index=40&list=PLA7-iYleFX4zkh2iMpJmgC54EgDfGvxug
40	Swaziland	https://www.youtube.com/watch?v=2KAV6wZM8ZU&list=PLA7-iYleFX4zkh2iMpJmgC54EgDfGvxug&index=41
41	Switzerland	https://www.youtube.com/watch?v=jbQdMhHkHIk&list=PLA7-iYleFX4zkh2iMpJmgC54EgDfGvxug&index=42
43	Ukraine	https://www.youtube.com/watch?v=3fR2V5wjh8Y&index=44&list=PLA7-iYleFX4zkh2iMpJmgC54EgDfGvxug
44	Venezuela	https://www.youtube.com/watch?v=_bPmSxNQh9s&index=45&list=PLA7-iYleFX4zkh2iMpJmgC54EgDfGvxug
45	Wales	https://www.youtube.com/watch?v=U7tjfg6RM8Y&index=46&list=PLA7-iYleFX4zkh2iMpJmgC54EgDfGvxug

F URLS OF THE PIANO COMPETITION VIDEOS

Appendix F provides the links to the videos of the finals of 10 piano competitions.

Table F.1: URLs of the piano competition videos

AARHUS Competition 2015		
1. Joshua Han	Beethoven Piano Sonata No. 27 in E minor, Op. 90-2	https://www.youtube.com/watch?v=skUgfD4ZpUQ
2. George Harliono	Chromatic Fantasy and Fugue	https://www.youtube.com/watch?v=D3UIWgZofIg
3. Elizaveta Klyuchereva	Rondo in D Major, K.485	https://www.youtube.com/watch?v=VC_KzIIju5c
Chopin2010		
1. Yulianna Avdeeva	Concerto in E minor, op. 11	https://www.youtube.com/watch?v=CHJ_dl-ouTo
2. Ingolf Wunder	Concerto in E minor, op. 11	https://www.youtube.com/watch?v=yDe39VF_V44
3. Danii Trifonov	Concerto in E minor, op.11	https://www.youtube.com/watch?v=u4siREIID-o
Chopin 2015		
1. Seong Jin Cho	Piano concerto in E minor, op.11	https://www.youtube.com/watch?v=6140SsDS734
2. Charles Richard	Piano concerto in F minor, op.21	https://www.youtube.com/watch?v=rawF-OsPE70
3. Kate Liu	Piano concerto in E minor, op.11	https://www.youtube.com/watch?v=rs8rrW4s_rs
Van Cliburn 1993		
1. Simone Pedroni	Rachmaninov Rhapsody on a Theme of paganini	https://www.youtube.com/watch?v=DevG2ENlTbw
2. Valery Kuleshof	Rachmaninov concerto no. 3 in D minor	https://www.youtube.com/watch?v=DevG2ENlTbw
3. Christoper Taylor	Brahms concerto no. 2 in B flat major 1st	https://www.youtube.com/watch?v=DevG2ENlTbw
Cliburn Junior 2015		
1. Alin Beysembayev	Tchaikovsky piano concerto no. 1 in B-flat minor, op. 23	https://www.youtube.com/watch?v=VxF9pvSolr4
2. Arsenii Muni	Grieg Piano concerto in A minor, op. 16	https://www.youtube.com/watch?v=ff9uXDHBZds
3. Youlan Ji	Chopin Piano concerto no. 2 in F. minor. Op. 21	https://www.youtube.com/watch?v=egxeIoMh4Qs
Dublin 2012		
1. Nikolay Khozyainov	Rachmaninov Piano Concerto No. 3	https://www.youtube.com/watch?v=WYEgsxXMQOU
2. Jiayan	Tchaikovsky Concerto no. 1	https://www.youtube.com/watch?v=L40bHKhcaGk
3. Alexander Berstein	Tchaikovsky Concerto no. 1	https://www.youtube.com/watch?v=FVkFSt1LSMg
8 Fransz Liszt Competition 2008		
1. Vitaly Pisarenko	Liszt Concerto no. 1/ Danse	https://www.youtube.com/watch?v=Kg4gcUzvDkg
2. Nino Gvetadze	Piano concert no. 2 ina a Major/Chopin	https://www.youtube.com/watch?v=r1rQG9k00NM
3. Anzelika Fuks	Piano concert no. 1 in a Major/Chopin	https://www.youtube.com/watch?v=-3EmmUE8UQQ
Geneva 2014		
1. Ji Yeong Mun	Beethoven concerto no. 4 in G major, opus. 58	https://www.youtube.com/watch?v=Ck7DBZpcKnY
2. Pallavi Mahidhara	Prokofiev concerto no. 3 in C major, opus 26	https://www.youtube.com/watch?v=AVKm7MfgPoA
3. Honggi Kim	Beethoven concerto no. 4 in G major, opus. 58	https://www.youtube.com/watch?v=RmE6EoS6GGI
Rubinstein 2014		
1. Antonii Baryshevskyi	Prokofiev - concerto no. 2 in G minor opus 26	https://www.youtube.com/watch?v=LEKDmWV7pk8
2. Steven Li	Prokofiev - concerto no. 2 in G minor opus 26	https://www.youtube.com/watch?v=ZTcFzDn1zUg
3. Cho Seong Jin	Tchaikovsky concerto no. 1 in B-flat minor. Op. 23	https://www.youtube.com/watch?v=9_nx3TIbfok
Walace Competition 2015		
1. Delvan Auckland	Ballade no.1 in G minor, op. 23 Granados: allegro de concierto, op. 46	https://www.youtube.com/watch?v=MDfFIooV-Wo
2. Modi Deng	Piano sonata no. 9 in D, K, 311:I. Allegro con spirito	https://www.youtube.com/watch?v=nocr34oEZlg
3. Ji Hyun Sohn	Piano Sonata in B minor, H. XVI No. 32: I, allegro moderato	https://www.youtube.com/watch?v=TvZASWW_t3Q

G URLS OF THE JKT48 PROFILE VIDEOS

Appendix G provides links to the profile videos of the JKT48 competition.

Table G.1: URLs of the JKT48 videos

No	Participants	Youtube URLs
1	Nabilah	https://www.youtube.com/watch?v=V5KloQ3CnFw&index=1&list=RDV5KloQ3CnFw
2	Ve	https://www.youtube.com/watch?v=_gQLROhYrVQ&list=RDV5KloQ3CnFw&index=3
3	Haruka	https://www.youtube.com/watch?v=7MgAqCz7KoI&list=RDV5KloQ3CnFw&index=4
4	Kinal	https://www.youtube.com/watch?v=8v2G6B2xCVc&list=RDV5KloQ3CnFw&index=5
5	Ayana	https://www.youtube.com/watch?v=_lFWHZXnxus&index=6&list=RDV5KloQ3CnFw
6	Naomi	https://www.youtube.com/watch?v=dcjkioDlseM&list=RDV5KloQ3CnFw&index=7
7	Yuvia	https://www.youtube.com/watch?v=k6xfRswRmLw&index=8&list=RDV5KloQ3CnFw
8	Beby	https://www.youtube.com/watch?v=a_vqIQfoZdI&list=PLqQ7E8cz91tACcoZ_RB3c3VZihSkAMgom&index=4
9	Dhike	https://www.youtube.com/watch?v=okOUqx3KG9E&list=PLqQ7E8cz91tACcoZ_RB3c3VZihSkAMgom&index=6
10	Frieska	https://www.youtube.com/watch?v=b6479b2dEmo&list=PLqQ7E8cz91tACcoZ_RB3c3VZihSkAMgom&index=7
11	Gaby	https://www.youtube.com/watch?v=evHk6weXN3M&index=8&list=PLqQ7E8cz91tACcoZ_RB3c3VZihSkAMgom
12	Ghaida	https://www.youtube.com/watch?v=JegelqN_fIQ&index=9&list=PLqQ7E8cz91tACcoZ_RB3c3VZihSkAMgom
13	Jeje	https://www.youtube.com/watch?v=U_peKsDkNfI&index=11&list=PLqQ7E8cz91tACcoZ_RB3c3VZihSkAMgom
14	Shania	https://www.youtube.com/watch?v=L58a3QUkhJw&list=PLqQ7E8cz91tACcoZ_RB3c3VZihSkAMgom&index=17
15	Uty	https://www.youtube.com/watch?v=K1idtSilPpM&index=22&list=PLqQ7E8cz91tACcoZ_RB3c3VZihSkAMgom
16	Viny	https://www.youtube.com/watch?v=gMAsQaE7qVs&list=PLqQ7E8cz91tACcoZ_RB3c3VZihSkAMgom&index=23
17	Yona	https://www.youtube.com/watch?v=q2FXrsVDb-A&list=PLqQ7E8cz91tACcoZ_RB3c3VZihSkAMgom&index=24
18	Hanna	https://www.youtube.com/watch?v=GHoae_hYyMI&index=27&list=PLqQ7E8cz91tACcoZ_RB3c3VZihSkAMgom
19	Lidya	https://www.youtube.com/watch?v=wBMwKQjzkK8&index=29&list=PLqQ7E8cz91tACcoZ_RB3c3VZihSkAMgom
20	Sinka	https://www.youtube.com/watch?v=iRDS8kq32AQ&list=PLqQ7E8cz91tACcoZ_RB3c3VZihSkAMgom&index=36
21	Sisil	https://www.youtube.com/watch?v=hwqjJBRaHFE&index=37&list=PLqQ7E8cz91tACcoZ_RB3c3VZihSkAMgom
22	Chikarina	https://www.youtube.com/watch?v=1VcJ36nBM4o&list=PLqQ7E8cz91tACcoZ_RB3c3VZihSkAMgom&index=40
23	Shani	https://www.youtube.com/watch?v=eiK9amu-RZU
24	Sendy	https://www.youtube.com/watch?v=1in1PDMCr3Y
25	Melody	https://www.youtube.com/watch?v=q5HNMTRrBIM&index=13&list=PLqQ7E8cz91tACcoZ_RB3c3VZihSkAMgom
26	Rona	https://www.youtube.com/watch?v=nMhVbAZSqOo&list=PLqQ7E8cz91tACcoZ_RB3c3VZihSkAMgom&index=33
27	Dessy	https://www.youtube.com/watch?v=ym5X95V9sxg&index=45&list=PLqQ7E8cz91tACcoZ_RB3c3VZihSkAMgom
28	Michele	https://www.youtube.com/watch?v=VxBHz6KY4YA&index=50&list=PLqQ7E8cz91tACcoZ_RB3c3VZihSkAMgom
29	Andela	Revoked
30	Bonita	Revoked
31	Elaine	Revoked
32	Nissa	Revoked
33	Tata	Revoked

H JKT48 VIDEO RATINGS

Appendix H provides the video ratings of the JKT48 profile videos, averaged over the participants. The ILT traits 1 to 38. (Table 5.1 lists the names of the traits.)

Table H.1: JKT48 Video Ratings averaged over participants for ILT traits 1 to 19

Group																				
A	Video	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
	Shani	5.42	5.38	5.86	5.76	5.57	5.47	5.11	4.96	4.85	5.02	5.09	5.05	4.88	6.07	6.50	5.57	5.81	6.64	4.00
	Sendy	4.49	4.52	4.78	3.89	5.30	4.98	4.73	3.37	3.53	3.58	3.43	3.48	3.48	4.88	4.94	4.49	4.16	4.48	3.02
	Rona	3.98	4.25	4.34	4.38	4.90	4.62	4.67	3.39	3.67	3.59	3.66	3.58	3.66	4.46	5.19	4.13	4.69	5.11	4.31
	Nissa	4.29	4.30	4.39	4.44	4.58	4.53	4.73	3.56	3.50	3.69	3.73	3.74	3.81	4.63	4.46	4.34	5.11	5.47	4.44
	naomi	5.00	5.65	5.33	5.84	5.92	5.60	5.80	5.04	5.12	4.97	5.28	4.51	4.49	5.60	5.48	5.68	4.78	5.35	5.03
	Nabilah	3.54	4.68	3.91	3.87	3.97	4.19	3.85	3.97	4.16	4.96	4.05	3.77	3.96	4.13	3.62	3.61	4.84	5.22	4.84
	Michelle	5.62	5.47	5.72	5.35	5.61	5.79	5.76	4.63	4.30	4.42	4.20	4.26	4.17	5.56	5.46	5.04	5.03	5.31	4.55
	Melody	4.93	5.07	5.09	5.35	5.17	5.54	5.51	4.52	4.84	4.71	4.76	4.63	4.71	5.19	4.47	4.75	4.55	4.97	4.69
	Lidya	6.38	5.85	5.88	5.92	5.74	5.31	5.40	6.12	6.14	6.18	6.30	5.85	5.91	5.74	6.09	5.75	5.22	5.40	5.31
	Kinal	5.07	5.35	6.28	5.35	5.19	5.31	5.27	5.64	5.60	5.45	5.74	5.51	5.73	7.26	6.85	6.38	6.46	7.04	5.85
	Jeje	2.93	3.97	4.52	3.90	4.00	4.11	4.00	2.93	3.27	2.94	2.66	2.71	2.78	4.42	4.40	4.34	5.02	6.49	4.33
B	Uty	5.80	6.30	6.00	6.00	5.20	5.20	5.50	5.90	6.10	5.90	5.90	5.90	5.90	6.10	6.10	5.67	4.80	4.70	4.56
	Frieska	3.68	4.26	4.07	4.54	4.34	4.53	4.62	3.95	4.40	3.84	4.01	4.21	4.47	4.11	4.05	3.48	3.53	4.24	4.27
	Yuvia	3.49	4.49	5.02	4.27	5.41	5.18	4.85	3.04	3.12	3.05	3.24	2.79	2.73	4.86	5.10	3.88	4.35	6.01	2.87
	Yona	5.69	5.81	5.96	6.19	5.57	5.50	5.67	6.07	6.29	6.03	5.99	5.80	5.92	5.69	5.74	5.94	4.73	4.92	4.70
	Viny	5.39	5.91	6.36	6.06	6.16	6.75	6.45	4.84	4.84	4.80	5.02	4.44	4.86	6.88	6.80	6.12	4.79	5.01	4.08
	Ve	6.27	5.78	6.21	6.12	6.45	6.18	6.02	5.52	5.50	5.57	5.93	5.84	5.79	6.15	6.18	5.90	4.95	5.40	4.55
	Tata	5.35	5.16	5.39	5.38	5.95	5.62	5.18	3.49	3.33	3.40	3.90	3.78	3.78	4.84	4.79	4.33	3.59	5.10	3.25
	Sisil	4.40	3.91	4.43	4.30	4.63	4.17	4.15	4.43	4.43	4.57	4.53	4.68	4.62	5.30	5.27	4.88	4.09	4.61	4.50
	Sinka	3.92	4.88	4.75	4.33	5.20	5.81	5.93	2.84	2.62	2.74	2.69	2.62	2.40	4.62	3.88	3.13	3.97	5.31	3.62
	Shania	5.49	5.16	5.67	5.38	5.79	5.47	5.15	5.05	4.06	4.84	4.90	4.95	5.06	5.73	5.56	4.85	5.14	5.36	4.54
C	Haruka	4.79	4.93	5.20	5.39	6.43	5.77	6.07	3.22	3.61	3.40	3.39	3.43	3.25	6.22	5.30	4.14	4.12	4.77	3.78
	Hanna	4.87	5.12	5.34	5.58	5.86	5.71	5.28	4.49	4.42	4.07	4.67	4.64	4.45	5.90	5.76	5.26	5.15	5.56	4.97
	Ghaida	4.96	5.04	4.97	5.10	5.03	4.66	5.03	5.61	5.56	5.35	5.49	5.13	5.25	3.96	4.11	4.09	4.40	4.69	4.57
	Gaby	4.78	4.79	5.49	5.75	5.62	5.16	5.64	3.98	3.78	4.00	3.88	3.08	3.42	5.58	5.57	4.93	4.77	5.49	5.02
	Elaine	5.79	5.53	5.48	5.94	5.87	5.86	5.96	5.17	5.07	4.97	5.07	4.64	4.71	5.84	5.59	5.47	5.68	6.02	5.27
	Dhike	5.06	4.27	4.76	4.72	5.46	4.64	5.29	3.74	4.04	3.96	4.03	3.96	4.22	5.09	4.29	4.18	4.39	4.43	3.43
	Desy	5.62	5.06	5.58	5.77	5.64	5.64	5.12	4.99	5.11	4.94	4.69	4.78	4.88	6.10	6.20	5.51	5.36	6.00	5.60
	Chikarina	4.71	4.68	4.98	4.78	4.97	5.00	4.90	4.29	4.23	4.24	4.32	4.06	3.98	5.13	5.34	4.77	4.84	4.71	4.40
	Baby	4.83	5.21	5.55	5.64	4.86	5.27	5.25	5.81	5.57	5.84	5.75	5.79	5.75	6.36	6.13	6.07	5.66	6.03	5.87
	Ayana	5.36	4.97	5.55	5.81	6.55	5.68	5.77	4.25	4.29	4.21	4.31	4.17	4.19	5.21	4.80	4.68	4.31	4.45	3.85
	Andela	4.83	5.20	5.32	5.47	6.22	5.98	5.88	4.76	4.64	4.71	4.65	4.52	4.34	4.97	5.16	5.09	4.94	5.29	4.52

Table H.2: JKT48 Video Ratings averaged over participants for ILT traits 20 to 38

Group																				
A	Video	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38
	Shani	5.91	6.24	6.11	6.56	4.94	4.82	4.88	4.28	5.17	4.39	4.71	5.52	3.71	3.64	6.71	6.16	5.91	6.24	6.54
	Sendy	4.62	5.39	4.78	4.89	4.65	4.62	4.59	4.76	4.68	4.52	4.32	4.06	3.80	3.94	5.23	4.60	3.88	5.51	6.47
	Rona	5.97	6.12	5.16	5.72	5.27	5.28	5.15	5.54	5.68	6.07	5.70	4.20	3.78	3.52	5.86	5.22	4.41	6.07	7.46
	Nissa	5.54	5.98	5.05	5.02	5.17	5.06	4.85	5.07	4.78	4.62	5.07	4.29	3.77	3.82	5.10	5.23	4.74	4.03	4.53
	naomi	5.94	5.28	5.52	5.55	4.68	4.26	4.47	4.03	4.72	4.31	4.22	4.62	4.07	4.17	5.27	5.69	5.12	5.86	6.13
	Nabilah	4.63	5.92	4.24	4.56	4.89	4.92	4.90	4.77	4.45	5.38	5.38	4.92	3.69	3.23	3.97	5.09	4.53	5.24	4.85
	Michelle	5.54	5.36	5.37	5.77	4.54	3.87	4.22	5.10	4.87	4.76	4.29	4.34	3.72	4.06	7.24	6.03	4.59	5.97	7.61
	Melody	4.28	4.98	4.29	4.90	4.10	4.58	3.66	4.42	4.07	4.98	3.58	4.21	3.27	5.06	6.28	5.20	4.56	5.39	6.46
	Lidya	5.28	6.43	5.81	5.84	5.41	4.62	5.68	4.75	4.61	4.89	3.86	5.64	3.99	3.69	5.13	5.37	5.61	5.93	6.51
	Kinal	7.19	6.96	6.96	6.42	6.54	5.78	6.28	5.24	6.10	6.13	6.68	5.56	4.46	3.50	6.60	5.77	6.13	5.46	6.19
	Jeje	7.13	6.55	4.82	4.77	4.22	4.19	4.38	4.89	4.59	4.55	6.22	3.20	4.28	3.80	5.10	4.38	3.46	4.28	5.52
B	Uty	4.40	5.20	5.80	5.50	4.70	4.20	4.40	4.40	4.60	4.00	4.00	5.10	3.20	3.40	4.70	5.00	5.50	5.40	6.20
	Frieska	4.17	5.13	4.99	4.90	4.20	4.56	4.36	4.21	4.90	4.92	4.67	3.69	4.00	4.29	4.37	4.18	4.50	4.58	5.54
	Yuvia	6.41	5.71	4.21	5.23	4.13	4.71	4.30	4.02	4.18	4.27	6.75	2.92	3.58	3.33	6.31	5.15	3.11	5.17	6.14
	Yona	4.82	5.48	6.10	5.41	4.73	3.48	3.74	3.73	3.39	3.14	3.39	5.22	3.24	3.34	5.46	5.70	5.21	5.47	6.01
	Viny	6.47	5.98	6.11	5.78	4.15	3.96	3.95	4.04	3.90	3.33	5.43	5.04	3.95	4.06	6.88	6.26	5.28	4.87	5.51
	Ve	5.19	5.78	5.70	5.78	4.36	4.14	4.31	4.53	4.10	4.41	5.26	5.48	3.99	4.02	6.40	6.71	5.80	6.31	7.00
	Tata	5.52	5.37	4.74	5.62	4.21	3.85	3.91	3.97	4.58	5.05	5.17	3.93	4.55	3.92	6.32	5.65	4.54	5.49	6.70
	Sisil	4.80	5.55	5.66	4.65	4.66	5.10	5.07	5.38	4.81	5.31	4.37	4.03	4.40	3.42	4.30	4.04	4.68	3.96	5.25
	Sinka	7.33	6.19	4.90	4.82	3.09	3.55	2.78	2.78	3.35	3.35	6.65	3.19	3.26	3.41	7.62	5.86	3.99	4.24	6.40
	Shania	5.43	6.29	5.54	4.99	5.56	5.02	5.05	4.79	5.10	4.49	4.58	5.56	4.50	3.45	5.17	5.00	5.64	5.59	6.59
C	Haruka	7.13	5.28	5.03	5.68	4.31	4.79	3.84	3.66	4.45	4.63	5.40	3.05	3.71	4.77	7.06	5.46	3.54	4.88	7.39
	Hanna	6.97	6.21	5.94	5.95	4.81	5.32	4.53	4.97	5.32	4.30	6.04	4.47	3.90	3.98	7.17	5.98	4.58	5.40	6.22
	Ghaida	3.92	5.22	4.66	4.75	4.13	4.54	3.58	4.12	4.55	5.22	4.27	4.36	4.28	4.77	4.10	3.79	4.28	3.84	4.91
	Gaby	7.10	5.95	5.67	5.30	4.38	5.05	4.10	4.77	5.12	4.65	5.68	4.63	4.01	4.33	7.13	6.00	4.72	5.77	6.96
	Elaine	6.48	6.66	6.09	5.93	5.68	5.45	4.82	4.73	5.52	5.15	5.24	5.22	4.04	4.28	5.91	5.74	5.80	5.62	6.70
	Dhike	4.54	4.01	3.96	4.84	4.19	4.87	4.47	5.19	5.02	4.62	4.45	4.39	4.45	5.19	5.86	4.43	4.40	4.28	5.41
	Desy	6.84	6.18	5.71	5.33	4.78	5.86	5.40	5.28	5.48	5.65	5.55	5.26	4.21	4.14	7.16	5.79	5.20	6.20	6.86
	Chikarina	5.63	5.54	5.06	5.63	4.32	5.27	4.56	4.78	5.09	4.87	5.14	4.70	3.97	3.92	6.12	5.06	5.13	4.53	6.20
	Baby	6.52	6.28	6.54	5.93	5.71	5.50	5.06	5.41	5.87	5.16	5.61	5.46	3.89	3.70	6.99	5.69	5.66	5.74	6.23
	Ayana	4.60	4.19	4.10	4.63	3.77	4.02	3.41	4.08	4.51	4.36	3.83	3.75	3.41	4.60	5.69	5.13	4.34	4.86	6.39
	Andela	5.90	5.80	5.71	5.00	4.18	4.99	4.60	4.72	4.61	4.70	4.65	4.71	3.92	3.82	6.72	5.58	5.54	6.30	6.91

I JKT48 QUALTRICS SURVEY

Appendix I lists the successive screens of the JKT48 survey operated by Qualtrics.

TILBURG UNIVERSITY

Dear Participant,

Thank you for being a participant for this survey. This survey is created to measure leadership traits person depicted in videos according to implicit leadership theory (ILT) developed by Robert Lord [et.al] (1984).

In the survey, we would like you to **rank the leadership characteristics of 11 persons** based on short fragments of their video appearances. The duration of each fragment is 5 seconds. For each video you are requested to rate 38 leadership features based on ILT by means of sliders.

We thank you in advance for your participation.

Regards,
Wilma and Tara

TILBURG UNIVERSITY

Before turning to the actual survey, we start by asking you some questions.

>>

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What is your gender?

Male

Female

>>

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How old are you?

>>

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What is your nationality?

>>

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What are you currently studying?

- Elementary School
- High School
- MBO
- Bachelor

Master

PhD

Others

>>

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In the current questionnaire, the word **leader**, will refer to a person in an organizational position who is successful on leading groups of people.

Imagine that you are watching the TV with no sound, you see a person and you immediately think "there is a leader". Which of personality traits do you believe are characteristic to a successful **leader**?

Below is a list of characteristics and their explanation

Characteristics	**Meaning**
Understanding	The ability to learn, judge, make decision
Sincere	Free from pretense or deceit; proceeding from genuine feelings
Compassionate	Feeling or showing sympathy and concern for others
Helpful	Giving or ready to give help; feeling or showing sympathy and concern for others

Sensitive	Having or displaying a quick and delicate appreciation of the other's feelings
Warm	Having, showing or expressing enthusiasm, affection or kindness
Forgiving	Ready and willing to forgive
Intelligent	Having or showing intelligence especially of a high level
Clever	Quick to understand, learn and devise or apply ideas
Knowledgeable	Intelligent and well informed
Educated	Having been intellectual typically at a school or university
Wise	Having or showing experience, knowledge and good judgement
Intellectual	Relating to the intellect
Motivated	Provide someone with a motive for doing something
Dedicated	Devoted to a task or purpose
Hard-working	Tending to work with energy and commitment
Bold	Showing an ability to take risks; confident and courageous
Dynamic	Process characterized by continuous change, activity or progress
Strong	Having the ability to perform a physically demanding task
Energetic	Showing or involving great activity or vitality
Confident	Feeling or showing confidence in oneself
Determined	Having made a firm decision and stick to it
Charismatic	Exercising a compelling charm that inspires devotion in others
Domineering	Overbearing, authoritarian

Pushy	Excessively or unpleasantly self-assertive or ambitious
Dominant	Most important, powerful or influential
Manipulative	Characterized by unscrupulous control of a situation or person
Conceited	Excessively proud of oneself
Selfish	Lacking consideration for others
Loud	Producing or capable of producing much noise; easily audible
Credible	Able to be believed
Stressed	Suffering from anxiety, sorrow or pain
Uncertain	Not able to be relied on, unsure, doubtful, undecided, indecisive, hesitant
Smiling	Expression of smile
Likeable	Pleasant, friendly and easy to like
Competent	Having the necessary ability, knowledge or skill to do something successfully
Attractive	Pleasing or appealing to the senses
Feminine	Having qualities or appearance traditionally associated with women, especially delicacy and prettiness

Please shift the slider to a position that represents your opinion. The slider ranges from 1-9 with 1 = "not at all characteristic" and 9 = "extremely characteristic"

Not at all characteristic		Extremely characteristic
1	5	9

Understanding

Sincere

Compassionate

Helpful

Sensitive


Warm
Forgiving
Intelligent
Clever
Knowledgeable
Educated
Wise

Intellectual

Motivated

Dedicated

Hard-working

Bold

Dynamic

Strong


Energetic
Confident
Determined
Charismatic
Domineering
Pushy
Dominant


Manipulative
Conceited
Selfish
Loud
Credible
Stresses
Uncertain


Smiling
Likeable
Competent
Attractive
Feminine
>>

TILBURG UNIVERSITY

In this part you will watch and rate the leadership characteristics of 32 videos of girls. The duration of each video is 5 seconds and is accompanied by the 38 leadership characterisitics that you saw on the previous pages. The videos are muted and you are allowed to watch it multiple times while providing your ratings.

Please rate the leadership characteristics of the girls in the video by shifting the slider to the position that represents your opinion.

>>


Lidya
PEMILIHAN MEMBER SINGLE KE-10 JKT48
LIDYA
MAULIDA
GIVE ME A CHANCE
0:00 / 0:05

Please rate the leadership characteristics of the girl in the video by shifting the slider to the position that represent your opinion.

Not at all characteristic		Extremely characteristic
1	5	9

Understanding

Sincere

Compassionate

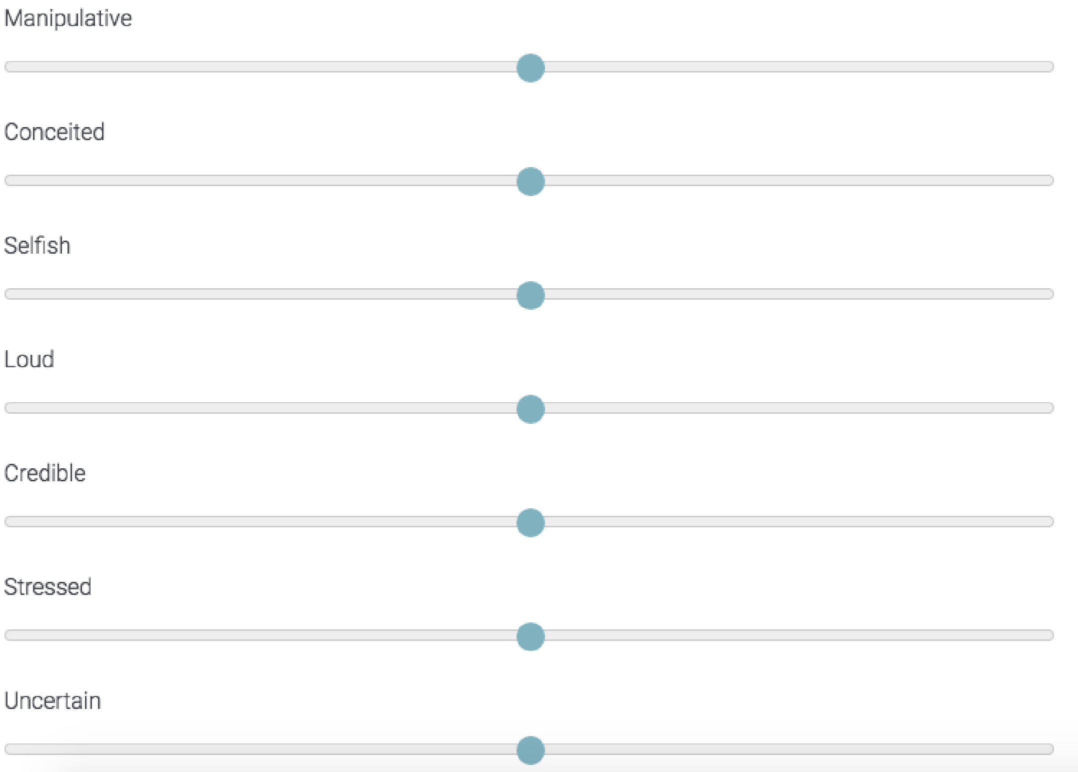
Helpful

Sensitive


Warm
Forgiving
Intelligent
Clever
Knowledgeable
Educated
Wise


Intellectual
Motivated
Dedicated
Hard-working
Bold
Dynamic
Strong


Energetic
Confident
Determined
Charismatic
Domineering
Pushy
Dominant


Manipulative
Conceited
Selfish
Loud
Credible
Stressed
Uncertain


Smiling
Likeable
Competent
Attractive
Feminine
>>

J LIST OF THE ILT FACTORS AND THE ILT ITEMS

Appendix J provides list of the ILT Factors and the ILT Items based on Trichas and Schyns study (2012).

Table J.1: List of the ILT Factors and the ILT items of Trichas and Schyns study (2012)

No	Factors Phase 1	Items	Factors Phase 2	Items
1	Intelligence	Clever, Intelligence, Knowledgeable, Educated, Wise	Intelligence	Clever, Intelligence, Knowledgeable, Educated, Wise
2	Sensitivity	Compassionate, Sensitive, Helpful, Forgiving, Sincere, Understanding, Warm	Sensitivity	Compassionate, Sensitive, Helpful, Sincere, Understanding, Warm
3	Tyranny	Conceited, Selfish, Manipulative, Loud, Uncertain, Pushy,	Tyranny	Conceited, Selfish, Manipulative, Uncertain, Pushy, Domineering, Stressed, Dominant
4	Dynamism	Confident, Determined, Dynamic, Energetic	Dynamism	Confident, Determined, Dynamic, Energetic, Bold
5	Likeability	Likeable, Smiling Sympathetic, Charming, Outgoing, Irritable	Likeability	Likeable, Smiling
6	Masculinity	Femininity/Masculinity, Female/Male Attractive	Masculinity	Femininity/Masculinity, Female/Male, Attractive
7	Dedication	Motivated, Dedicated, Hardworking Competent	Dedication	Motivated, Dedicated, Hardworking,
8	Dominance	Motivated, Dedicated, Selfish	Potency	Intellectual, Wise, Intense, Strong
9	Social Skills	Extraverted, Expressiveness, Sociable, Enthusiastic, Antisocial		
10	Credibility	Decisive, Foxy, Sympathetic, Credible, Honest, Trustworthy		

SUMMARY

Setting the scene is important for every research topic. Ours is no exception. Therefore, we reiterate our own introduction which says it all. The first scene of our research is as follows. A selection committee is willing to receive the first candidate for the recently established professorship of data science in society. The members of the committee are well prepared by a university trainer from whom they learned that some individuals might make a big impression on other people, whereas others do not. Frequently, charismatic individuals benefit from their impressive appearances in an election procedure, a contest, or a competition. But to what extent do such persons really have a clear advantage over the other candidates? The university trainer is a professional lecturer. She had warned the members of the committee for fast conclusions and stressed that keeping a balanced consideration is always better. However, a balanced consideration takes time, and first impressions can be formed in a short period of time, say less than 30 seconds (cf. Ambady & Rosenthal, 1992). First impressions are often formed subconsciously using facial appearances (cf. Bar et al., 2006; Olivola & Todorov, 2010; Tom et al., 2010). As every well-trained candidate knows: facial appearance has been shown to have a large influence on impression formation. To be more precise facial attractiveness is associated with positive traits and facial unattractiveness with negative traits (cf. Miller, 1970). Thus, facial expressions are known to affect impression formation (see Bar et al., 2006). Now the question arises: how can a candidate use the facial expressions in a beneficial way in a competitive setting? As the above considerations show, the study of the power of facial expressions is hampered by the possible distorting effect of context. Without controlling for context, it is hard to interpret measurements of facial expressions. Therefore, in this thesis we focus on the study of the power of facial expressions in a restricted context, namely the context of competitions. As pointed out by Ekman, competitions are associated with specific display rules. For example, whereas winners in American sports may smile, the winner of a Miss World contest must cry (Boucher, 1974).

Our experiments will focus on the analysis of facial expressions in four competitive contexts: female pageant contests, male pageant contests, a music contest, and a leadership contest. We assume that within each of these contests and contexts, the display rules are fixed. For instance, in a pageant contest, the display rule may be to smile or to transmit a positive expression. Alternatively, during piano concerts the display rule may dictate the performer to exhibit a range of facial expressions that are congruent with the emotional spirit of the music. Finally, in a competitive situation were individuals are assessed on their leadership skills, serious expressions are assumed to be prevalent. The available computational tools allow us to perform objective analyses of facial expressions. In combination with the setting of the context that is assumed to constrain the display rules, we are ready to formulate our problem statement (PS). The problem statement of which the gist is given above is the point of departure for four separate research questions.

RQ1: *To what extent do facial expressions contribute to the attractiveness ratings in relation to femininity?*

RQ2: *To what extent do thin slices of facial expressions contribute to the attractiveness of males?*

RQ3: *To what extent do facial expressions allow for the identification of winning musicians?*

RQ4: *What is the relation of dynamic facial expressions to leadership assessment?*

The answers to the research questions enable us to formulate our conclusion to the problem statement.

Chapter 1 introduces the research topic by describing the context of facial expressions. A different context may lead to a different reaction from the same facial expressions. Our research domain focusses on four competitive contexts. We explain the facial action coding system (FACS) for compound facial expressions. The chapter introduces automatic coding of facial action using three automatic facial coding systems. Finally, the chapter formulates the problem statement, including the resultant research questions and the corresponding research methodology used to answer them.

Chapter 2 answers RQ1. The Chapter describes our study by performing a digital analysis of the facial expressions of videos of the Miss World 2013 contestants. We analysed three types of expressions in isolation and in combination with femininity: (i) facial expressions (represented by facial expression descriptors), (ii) smiling, and (iii) emotional expressions. The scores awarded by the Miss World judges to the videos of the contestant serve as an independent measure of attractiveness. We perform two analyses. In a correlation analysis the three types of expressions are correlated with the attractiveness judgement scores to determine their relation with attractiveness. In a predictive analysis, we train random decision forests on the task of predicting the attractiveness judgement scores in a leaving-one-out cross validation procedure. The results of the prediction analysis revealed that facial expressions contribute to facial attractiveness, but only in combination with femininity. In contrast, emotional expressions in combination with femininity do not contribute to attractiveness. These findings indicate that facial expressions contribute to female attractiveness, when considered in combination with sexual dimorphism.

Chapter 3 answers RQ2. The chapter presents survey and computational analyses of Mister World 2014 contestants, in order to determine static and dynamic cues to male attractiveness. We asked 365 participants to assess the attractiveness of images or video sequences (thin slices) taken from the profile videos of the Mister World 2014 contestants. Each participant rate the attractiveness on a 7-point scale, ranging from *very unattractive* to *very attractive*. In addition, we performed computational analyses of the landmark representations of faces in images and videos to determine which types of static and dynamic facial information predict the attractiveness ratings. The survey study revealed that: (1) the attractiveness assessments of images and video sequences are highly correlated, and (2) the attractiveness assessment of videos was on average 0.25 point above that of images. The computational study showed (i) that for images and the video sequence, three established measures of attractiveness correlate with attractiveness, and (ii) mouth movements correlate negatively with attractiveness ratings. The conclusion of the study is that thin slices of dynamical facial expressions contribute to the attractiveness of males in two ways: (i) in a positive way and (ii) in a negative way. The positive contribution is that presenting a male face in a dynamic way leads to a slight increase in attractiveness rating. The negative contribution is that mouth movements correlate negatively with attractiveness ratings.

Chapter 4 answers RQ3. The chapter describes the study investigating to what extent visual ques are essential for winner identification in a piano competition. The aim of this chapter is to examine to which degree facial expressions provide such cues. Inspired by the main experimental procedure as executed by Tsay (2013), we train a linear classification model on the task of identifying the winner from thin slices (short video fragments) of the three finalists of ten prestigious international piano competitions. The facial expressions (facial action units) of the finalists are automatically extracted from the thin slices. Each finalist is represented by facial action unit estimates from a random sample of 180 frames of its thin slice. Evaluating the trained model in a cross validation procedure results in a correct identification of 0.43 averaged over the proportions. This performance clearly is above chance (0.33) and is close to that of human participants ($\approx$ 0.47). A thorough analysis of the contribution of individual facial action units reveals that Action Unit 12, the so-called "Lip corner pull" has the largest relative contribution to the prediction. Overall, our results suggest that facial expressions may form the main contribution to successful human visual-only identification of winning finalists in musical competitions. In summary, our findings suggest that computers can identify winners at a level that is near that of human participants.

Chapter 5 answers RQ 4. The chapter presents the investigation of the relation between facial expressions and leadership traits. Trichas and Schyns (2012) already aimed to determine how facial expressions influence leadership perceptions in terms of Implicit Leadership Theory (ILT). It inspired us to start our fourth study. We conducted a survey study on automatic coding of the facial expressions of the video sequences. In the survey study, we submitted a questionnaire to 45 participants to rate 38 of ILT features that occurred in a video of a leadership competition. Then we analysed the results by using canonical correlation, which clustered 38 features of ILTs. To be more precise, the canonical correlation clustered 38 features of the ILTs in six groups. After the correlation analysis, we applied a factor analysis with PCA to cluster the ILTs factor in the dimension of traits factors. The result suggested that 6 factors of our solutions were captured in the ILT survey. We also found that there are fine-grained relations between action units of facial expressions and leadership traits. Finally, we completed this chapter by a discussion and answered RQ4 based on the results of our analysis.

Chapter 6 provides a general discussion. We mention the strengths of our study, and describe points of improvement. Moreover, we relate the findings to the recent literature.

Chapter 7 completes the thesis by discussing our findings and providing conclusions, as well as their implications for facial expressions to be studied in the competitive settings in the future.

SAMENVATTING

Een selectiecommissie ontvangt de eerste kandidaat voor de onlangs ingestelde leerstoel Data Science. De leden van de commissie zijn goed voorbereid door een academische trainer die hen vertelde dat sommige kandidaten een grote indruk maken, terwijl andere kandidaten minder indruk maken. Veelal maken charismatische personen dankbaar gebruik van hun indrukwekkende uitstraling in een verkiezing of in een wedstrijd. In hoeverre hebben zulke personen een meetbaar voordeel ten opzichte van andere kandidaten? De academische trainer is een professioneel docent. Zij heeft de leden van de commissie gewaarschuwd voor het nemen van te snelle besluiten en benadrukte daarbij het belang van een gebalanceerde evaluatie van iedere kandidaat. Helaas is een gebalanceerde evaluatie niet eenvoudig. Eerste indrukken worden gevormd in minder dan 30 seconden (cf. Ambady & Rosenthal, 1992) en komen vaak onbewust tot stand mede op basis van gezichtsexpressies (cf. Bar et al., 2006; Olivola & Todorov, 2010; Tom et al., 2010). Zoals iedere doorgewinterde kandidaat weet is het gezicht van grote invloed op de vorming van een (eerste) impressie. Meer precies geformuleerd: aantrekkelijke gezichten worden geassocieerd met positieve persoonlijkheidseigenschappen en onaantrekkelijke gezichten met negatieve persoonlijkheidseigenschappen (cf. Miller, 1970). Gegeven het feit dat gezichtseigenschappen de vorming van een (eerste) indruk bepalen (zie Bar et al., 2006), is de wezenlijke onderzoeksvraag: op welke wijze kunnen kandidaten hun gezichtsexpressies benutten in een competitieve situatie? De voorgaande overwegingen laten zien dat de kracht van gezichtsexpressies afhankelijk is van de context. Om de kracht van gezichtsexpressies te kunnen bepalen is het vereist om de context zo veel mogelijk gelijk te houden. Om die reden wordt in dit proefschrift de kracht van gezichtsexpressies onderzocht in een min of meer constante context, te weten een competitieve context. Paul Ekman gaf voorbeelden van zogenaamde display rules die horen bij een specifieke context. Bijvoorbeeld, Amerikaanse sporters die een wedstrijd winnen zullen doorgaans lachen, terwijl de winnaars van een Miss World evenement moeten huilen (Boucher, 1974).

Onze experimenten richten zich op de analyse van gezichtsexpressies in vier verschillende competitieve contexten: een vrouwelijke schoonheidswedstrijd, een mannelijke schoonheidswedstrijd, een muzikale competitie, en een leiderschapscompetitie. Onze aanname is dat in deze vier competitieve contexten, de display rules hetzelfde zijn. In bijvoorbeeld een schoonheidswedstrijd is de *display rule* dat de winnaar lacht of een positieve emotie uitstraalt. In een muzikale competitie zal de uitvoerder gezichtsuitdrukkingen tonen die overeenkomen met de emotionele lading van het uitgevoerde muziekstuk. Tenslotte, zullen de kandidaten in een leiderschapscompetitie voornamelijk serieuze gezichtsexpressies tonen. De beschikbare computationele methoden voor de automatische analyse van gezichtsexpressies maken het mogelijk om objectieve metingen te verrichten van gezichtsexpressies. Gecombineerd met de vaststelling van een consistente context, leidt dit tot de formulering van een probleemstelling (PS). De probleemstelling is gebaseerd op de voorgaande beschrijving en vormt het vertrekpunt voor vier onderzoeksvragen (zie wezenlijke onderzoeksvraag hierboven).

RQ1: *In hoeverre dragen gezichtsexpressies bij aan de aantrekkelijkheidsoordelen in relatie tot vrouwelijkheid?*

RQ2: *In hoeverre dragen korte fragmenten van gezichtsexpressies bij aan mannelijke aantrekkelijkheid?*

RQ3: *In hoeverre kan de winnende musicus worden geïdentificeerd op basis van gezichtsexpressies?*

RQ4: *Wat is de relatie van dynamische gezichtsexpressies met leiderschapsoordelen?*

De antwoorden op deze onderzoeksvragen maken het mogelijk om een antwoord te formuleren op de probleemstelling.

Hoofdstuk 1 introduceert het onderzoeksonderwerp van dit proefschrift door in te gaan op de context van gezichtsexpressies. Verschillende contexten en situaties zijn verbonden met verschillende reacties op dezelfde gezichtsexpressies. Ons onderzoeksdomein richt zich op vier competitieve contexten. We leggen het *Facial Action Coding System* (FACS) uit in termen van gecombineerde gezichtsexpressies en de basisbouwstenen van gezichtsexpressies: *facial action units*. Het hoofdstuk introduceert automatische codering van gezichtsexpressies aan de hand van drie verschillende automatische coderingsmethoden. Het hoofdstuk wordt afgesloten met de formulering van de probleemstelling, alsmede de vier onderzoeksvragen en de corresponderende onderzoeksmethodologie ter beantwoording van de probleemstelling.

Hoofdstuk 2 geeft een antwoord op RQ1. Het hoofdstuk beschrijft de digitale analyse van de gezichtsexpressies van profielvideo's van Miss World 2013 kandidaten. We analyseerden drie typen van expressies: (i) lokale gezichtsexpressies (*facial action units*), (ii) glimlachen, (iii) emotionele gezichtsexpressies. De aantrekkelijkheidscores die werden toegekend aan de individuele kandidaten door de erkende Miss World beoordelaars fungeerden als maat voor aantrekkelijkheid. Er werden twee analysen uitgevoerd. In een correlatie-analyse werden de drie typen van expressies gecorreleerd met de aantrekkelijkheidscores. In een predictieve analyse werden *random decision forests* getraind op de predictie-taak met als invoer de expressies en de variabele "vrouwelijkheid" (seksueel dimorfisme) en als uitvoer de aantrekkelijkheidscores. De resultaten van de predictieve analyse lieten zien dat lokale gezichtsexpressies bijdragen aan de voorspelling van aantrekkelijkheid, maar enkel in combinatie met vrouwelijkheid. Dit was niet het geval voor emotionele gezichtsexpressies in combinatie met vrouwelijkheid. Deze bevindingen laten zien dat gezichtsexpressies bijdragen aan oordelen over vrouwelijke aantrekkelijkheid, maar enkel in combinatie met seksueel dimorfisme.

Hoofdstuk 3 geeft een antwoord op RQ2. Het hoofdstuk beschrijft gedrags- en computationele studies van afbeeldingen en fragmenten van profielvideo's van Mister World 2014 deelnemers, met als doel om de rol van statische en dynamische bijdragen aan de beoordeling van aantrekkelijkheid te bepalen. In het gedragsexperiment werden 365 participanten gevraagd de aantrekkelijkheid van afbeeldingen en videofragmenten van de Mister World 2014 kandidaten te beoordelen. Participanten gaven hun oordeel op een 7-punts schaal, waarvan de scores varieerden van "zeer onaantrekkelijk" tot "zeer aantrekkelijk". In de computationele studie werden de afbeeldingen en videos geanalyseerd op basis van zogenaamde *landmark* representaties van de gezichten van de Mister World kandidaten. De gedragsstudie onthulde dat: (1) de aantrekkelijkheidsoordelen van afbeeldingen en videofragmenten een zeer hoge correlatie lieten zien, en (2) de aantrekkelijkheidsoordelen van videofragmenten gemiddeld 0.25 punten hoger waren dan die van afbeeldingen. De computationele studie liet zien dat (i) voor afbeeldingen en videofragmenten, drie vastgestelde maten voor aantrekkelijkheid correleren met aantrekkelijkheid, en dat (ii) mondbewegingen negatief correleren met aantrekkelijkheidsoordelen. De conclusie van de studie is dat videofragmenten van dynamische gezichtsexpressies op een positieve en negatieve wijze bijdragen aan de aantrekkelijkheid van mannelijke kandidaten. De positieve bijdrage bestaat uit de lichte toename in aantrekkelijkheidsoordelen voor dynamische stimuli (videofragmenten) in vergelijking met statische stimuli (afbeeldingen). De negatieve bijdrage bestaat uit mondbewegingen die negatief correleren met de aantrekkelijkheidsoordelen.

Hoofdstuk 4 beantwoordt RQ3. Het hoofdstuk handelt over de mate waarin visuele *cues* bijdragen aan de identificatie van de winnaar van finalisten in een piano competitie. Het doel van het hoofdstuk is om te bepalen of gezichtsexpressies dergelijke visuele *cues* vormen. Geïnspireerd door het experiment van Tsay (2013), hebben we een lineaire patroonherkenner getraind op de herkenning van de winnaar uit korte videofragmenten van drie finalisten van tien internationale piano-competities. De gezichtsexpressies (*facial action units*) van de finalisten werden automatisch gecodeerd. Iedere finalist werd gerepresenteerd door een (min of meer) willekeurige steekproef van 180 frames van zijn of haar videofragment. De evaluatie van het getrainde model in een kruis-validatie procedure resulteerde in een proportie van correcte identificaties ter grootte van 0.43. Deze prestatie is duidelijk boven kansniveau (0.33) en is vergelijkbaar met dat van muzikale beginners en experts (ca. 0.47). Een gedegen analyse van de bijdragen van individuele *facial action units* onthulde dat AU12, de zogenaamde *Lip corner pull*, de grootste bijdrage leverde aan de predictie. Algemeen beschouwd, suggereren onze resultaten dat gezichtsexpressies een voorname bron vormen voor de succesvolle beoordeling van de winnaar. Dit was in ieder geval zo bij participanten in de experimenten van Tsay. Samengevat ondersteunen onze resultaten het idee dat computers de winnaars kunnen identificeren op een niveau dat vergelijkbaar is met dat van muzikale beginners en experts.

Hoofdstuk 5 beantwoordt RQ4. Het hoofdstuk beschrijft de bestudering van de relatie tussen gezichtsexpressies en leiderschapskenmerken. Een eerdere studie van Trichas en Schyns (2012) bestudeerde reeds hoe gezichtsexpressies de perceptie van leiderschap beïnvloeden. Hiertoe maakten ze gebruik van *Implicit Leadership Theory* (ILT). Onze vierde studie werd geïnspireerd door het werk van Trichas en Schyns en combineerde vragenlijsten met de automatische codering van gezichtsexpressies van kandidaat-leiders. In de vragenlijst-studie, werden 45 participanten gevraagd om 38 eigenschappen (ILT kenmerken) te beoordelen voor 11 kandidaten in een leiderschapscompetitie. Iedere kandidaat werd gepresenteerd door een videofragment. De resultaten van de vragenlijsten werden gevisualiseerd door middel van een correlatie analyse. De visualisatie liet een duidelijke clustering zien van ILT kenmerken. Toepassing van factor analyse (met PCA) resulteerde in 6 factoren. Een correlatie-analyse van de 6 factoren met de automatisch gecodeerde gezichtsexpressies (*facial action units*) van de in de vragenlijsten gebruikte videofragmenten leverde aanwijzingen op voor subtiele relaties tussen gezichtsexpressies en leiderschapseigenschappen. Het hoofdstuk besloot met een discussie van de resultaten en een antwoord op RQ4.

Hoofdstuk 6 beschrijft een algemene discussie. Meer concreet, beschrijft het hoofdstuk de positieve aspecten van de studie en specificeert het een aantal verbeterpunten. Bovendien worden de gevonden resultaten gerelateerd aan de recente literatuur.

Hoofdstuk 7 completeert het proefschrift met conclusies en een beschrijving van de implicaties voor de toekomstige bestudering van gezichtsexpressies in competitieve contexten.

CURICULUM VITAE

Wilma Latuny was born on April, 6 1978 in Ambon, Indonesia. She had her secondary school at SMA Negeri 1 Ambon. She is graduated with Bachelor of Engineering degree from University of Pattimura and received a Master of Science from Sam Ratulangi University. She then was appointed as junior lecturer at the University of Pattimura and she taught several subject courses, such as statistics and research methodology.

In 2011, Miss Latuny received a scholarship from the Netherlands Organisation for International Cooperation in Higher Education (NUFFIC) to pursue a Ph.D. program from the Netherlands. She completed her coursework and achieved the Master of Philosophy (M.Phil) degree from Maastricht School of Management (MSM) in 2012. Then, she joined Tilburg Centre for Cognition and Communication (TiCC) in Tilburg University, the Netherlands, to complete the remainder of her Ph.D. program. Her Ph.D. project titled "The Power of Facial Expressions" resulted in this thesis.

PUBLICATIONS

CONFERENCE PROCEEDINGS

Latuny, W., Postma, E.O., & van den Herik, H.J. (2015). Digital Analysis of Beautiful Facial Expressions. In H.J. van den Herik and J. Filipe (Eds.), *Proceedings of the 8th International Conference on Agents and Artificial Intelligence (ICAART 2016)*, Volume 2, pp. 407-414. SciTePress: Rome, Italy. ISBN 978-989-758-172-4

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